POLITECNICO DI TORINO

Master of Science in Computer Engineering

Master Degree Thesis

Exploiting the momentum effect in the cryptocurrency market: A machine learning-based trading system

Supervisor: prof. Luca Cagliero

Co-supervisor: Dr. Giuseppe Attanasio

Candidate: Gian Pietro Enzo Bellocca

Academic year 2019 – 2020

Abstract

Cryptocurrency trading has become more and more popular among private investors. According to recent studies on the underlying market, it has shown to be affected by the momentum effect. This poses the questions of whether such effect could be exploited by discretionary traders to make substantial profits and to what extent algorithmic strategies based on Machine Learning could improve trading performance. The present thesis work addresses the above-mentioned research questions. The investigation begins with one of the fundamental questions of finance, which is the possibility of predicting the price movements of financial assets. First, the theories of traditional finance are reviewed, up to behavioural finance, which defines the dynamics and characteristics of the momentum effect. After identifying these features in the cryptocurrency market, some hypotheses are developed and tested on the real data provided by a cryptocurrency exchange. Following the hypothesis testing, some trading simulations are performed which show that it is possible to generate profits by exploiting the momentum effect. A machine learning-based approach, which relies on classification, is then proposed to analyse the possibility of improving further trading performance and solve some issue previously detected. The results of a back-testing phase confirm the potential of the analysed strategy and show the effectiveness of ML in limiting the volatility of the equity.

Acknowledgments

Questa è stata forse la pagina più difficile da riempire di tutta la tesi.
Ho sempre avuto molta difficoltà ad esprimere i miei più vividi sentimenti nei confronti delle persone a me care. Spesso non trovare le parole o il momento più adatto farlo mi ha fatto risultare come una persona distaccata e che da poca importanza a chi gli sta vicino. Ma non c'è nulla di più lontano dalla verità.
Trovo quindi queste poche righe come una splendida occasione per farlo, potendo parlare senza filtri e potendo mostrare la mia gratitudine verso tutte quelle persone che hanno avuto il piacere e l'onere di accompagnarmi in questo percorso.
Ringrazio per prima la mia famiglia, spesso terreno di confronto e scontro, ma che mi ha aiutato a crescere sempre e ha gettato le basi della persona che sono oggi.
Ringrazio quelle persone che ci sono fin dall'inizio e che sono sempre rimasti al mio fianco, nonostante il tempo, la distanza, gli alti e i bassi che una vera amicizia può affrontare e che deve superare per chiamarsi tale.
Ringrazio tutte le persone che ho incontrato durante i miei studi e le mie prime esperienze nel mondo del lavoro, e che le hanno rese divertenti e stimolanti.
Ringrazio le persone che ho conosciuto in questi ultimi anni e che mi hanno accompagnato verso un nuovo capitolo della mia vita. Tra trasferimenti all'estero in città nuove ed esperienze fantastiche che sono felice di aver condiviso con voi. Siete diventate delle persone per me importanti e nonostante la distanza avrete sempre un posto nel mio cuore.
Infine, ringrazio Gian Pietro, che è riuscito ad arrivare fino a questo punto, tra mille difficoltà, e che mi ha sopportato per tutto questo tempo.

Grazie di cuore a tutti.

Contents

Chapter 1

Introduction

One of the most important and discussed topics in the field of finance is the possibility of predicting prices' movements. Several empirical tests and researches have been produced to verify if prices follow specific and predictable paths, or if they move in a completely random way. The reason for this great interest is that the predictability of asset prices would allow investors to obtain anomalous returns compared to the normal return of the market. Traditional and behavioural finance have deeply different opinions on this topic.

The models belonging to the traditional finance theory use a series of hypotheses which define the behaviour of investors and the conditions in which they operate, in order to understand the dynamics and shape the functioning of the financial markets. More specifically, many models require investors to be risk-averse and able to make rational choices with the aim of maximizing profits, without being influenced by other factors and with complete access to all the information available in the market. These types of models also require an effective arbitrage mechanism, which plays a critical role in determining the prices of the securities. In fact, when an arbitrage opportunity arises, which consists of the opportunity to earn by buying and selling the same asset at a higher and lower price respectively, it is essential that this opportunity is immediately exploited by investors. In this way the market will allow the prices to return to the right equilibrium immediately, not allowing an asset to be overvalued or undervalued for too long periods.

The assumptions formulated by traditional finance theory, however, often seem to be unrealistic. Moreover, in the 1980s, a large number of researchers began to experience a series of empirical results, incompatible with the price equilibrium and efficient market models developed before. These results include several effects such as the momentum, the reversal, the size and the January effect that were considered only anomalies by traditional finance. Anyway, the persistence of these anomalies, and the emergence of new ones, has led scholars to wonder if the models deriving from traditional finance are able to understand and describe the market dynamics and the movement of financial asset prices efficiently. Trying to answer to this issue, a new theory known as behavioural finance was formulated in the 1980s. This new theory is based on two fundamental pillars, the investor's psychology and the limits of arbitrage. The most important innovation of behavioural finance is to incorporate several concepts and studies from social sciences and psychology into the financial theory. Unlike traditional finance, that idealizes the investor as a rational entity, behavioural finance takes into account the thoughts, emotions and actions of real people. It is therefore based on the idea that investors do not always act rationally, and that their behaviours can influence the entire market, making it irrational. In particular, it is believed that irrationality derives from psychological biases, which influences the methodology used by people to create their expectations and make decisions. All these biases lead to cognitive errors, influencing the way people think, therefore one of the main aspects studied by behavioural finance is the influence of these biases on the investor and the whole market. Also, the idea that erroneous prices can only exist temporarily, as stated by traditional finance theory, is opposed by behavioural finance supporters, who say that deviations can persist for prolonged periods of time due to some limitations of the arbitrage mechanism. The fundamental concept on which this hypothesis is based is that arbitrage is not considered risk free and that the risk associated with arbitrage trading could discourage investors from undertaking this kind of operations, not allowing price correction.

Of particular interest, for this thesis, is the fact that irrational investors and the limits of arbitrage can lead to market inefficiency, whereby asset do not necessarily carry their fundamental value or follow a random walk, as argued by traditional finance theory. Differently, the assets could be priced using some predictable investment patterns, which can be exploited by the investors. This means that the implications of behavioural finance could lead to predictable asset prices, allowing the identification of trading strategies based on anomalous phenomena in the market such as the momentum effect and the reversal effect. In short, momentum effect refers to the positive autocorrelation of prices or the tendency for rising asset prices to rise further and falling prices to keep falling. On the contrary, the reversal effect refers to the phenomenon whereby asset prices show a negative autocorrelation, and therefore only after a prolonged period of deviation they revert and move back to their fundamental values. Various evidences of these two effects were found in several markets.

The purpose of this thesis is to understand if the cryptocurrency market is affected by the momentum effect, and if this can be exploited by investors in order to make substantial profits, first using a heuristic strategy and then proposing a machine learning-based approach, to analyse the possibility of improving further the trading performance and solve some issue previously detected. Initially, a theoretical verification of the momentum effect presence will be proposed, based on some evidence found in the cryptocurrency market, which can be explained thanks to the theory of behavioural finance and similarities found in other markets.

An empirical verification will then be performed, based on some hypotheses presented by Caporale and Plastun in their paper "Momentum effect in the cryptocurrency market after one-day abnormal returns" (2019)

1. The intraday behaviour of hourly returns is different on overreaction days compared to normal days
2. There is a momentum effect on overreaction days
3. There is a momentum effect the day after an overreaction day

The two researchers have revealed the presence of a momentum effect after a sharp change in the price of a cryptocurrency, called overreaction. Prices tend to move in the direction of the overreaction when it occurs, and this implies the existence of a momentum effect and the arise of exploitable profit opportunities. In order to verify the hypotheses presented by Caporale and Plastun and to generate an effective trading strategy an analysis of price trends has been performed and a heuristic algorithm has been developed and tested on historical cryptocurrencies data. The results obtained confirm the first two hypotheses and the possibility of generating profits using a trading strategy based on the developed heuristic algorithm. However, even if profitable, this strategy is not efficient if applied to real operativity, due to problems related to risk and difficult resources allocations. In particular the strategy tends to open a large number of positions

subjecting the equity to high volatility, due to difficulties in detecting the overreaction days in which the strategy must operate to exploit the momentum effect that occurs. Very often positions are opened on normal days considered to be overreaction day, increasing the number of trades and therefore the use of resources, decreasing profits and raising the level of risk.

To face this issue and the negative effect of volatility we propose the integration of machine learning that supports the detection of overreaction through the recognition of predictive pattern within the historical price series. A new detection system based on the ensemble of the heuristics algorithm and a classifier is introduced. Specifically, five different learning algorithms are tested, and their performance improved through a validation phase in order fine-tune the model hyperparameters. The reported results show an excellent ability of the classifier to accurately predict the days of overreaction, and the ability of the new strategy that uses the classifier in generate profits.

The most interesting results are obtained in portfolio back testing simulations, where the problem of risk and resource allocation is particularly stressed. In these simulations the ability to invest simultaneously in multiple cryptocurrencies is tested, trying to replicate the real conditions under which a portfolio operates. The use of machine learning techniques, integrated with the heuristic strategy, make the results in this scenario more efficient and so applicable in real contests. Machine learning significantly reduces the volatility of the equity thus making the trading system affordable by private investors. Furthermore, it slightly improves the overall pay-out by letting the trading system allocate larger portions of the equity to the most reliable trading signals.

Chapter 2

Cryptocurrency Market

The Cryptocurrency Market is a young and poorly structured Financial Market, with features and behaviours very distant from traditional markets, in which products such as stocks, bonds, currencies, commodities and derivatives are traded. However, in order to better appreciate the dynamics and peculiarities of the cryptocurrency market, it is first necessary to describe the whole Financial Markets environment in a more general way and describe the main features of a cryptocurrency.

2.1 Financial Markets

Financial Markets refer broadly to any marketplace where operators and institutions can trade financial products such as stocks, corporate and government bonds, currencies, commodities and derivatives. Started as a physical place, where different actors interest to trade met, with the introduction of modern ICT has evolved in a complex virtual platform, where intermediaries ensures the exchange of financial assets at the best market price, avoiding transaction risks. Financial Markets play a key role in facilitating the smooth functioning of the economy by allocating resources and creating liquidity for businesses and entrepreneurs and by matching the demand and supply of financial instruments.

The stock market is probably the most known market and it allows investors to buy and sell shares of publicly traded companies. It is important to distinguish between the primary and secondary market. In the former, companies sell their shares for the first time through an Initial Public Offer (IPO), in order to raise capital from external investors. In the latter, the investor can trade the shares after the IPO, enabling the replacement of public investor and the possibility of gains and losses due from the sale of shares.

Another important market is the bond market, often called debt market or fixed-income market, where an investor loans money for a defined period at a pre-established interest rate. The principal bond issuers are corporations, governments and municipals which generally use the proceeds from bonds to finance infrastructural improvements, maintain operations and pay down debts.

The forex and commodity market are the markets in which participants can buy, sell, exchange, and speculate on currencies and raw or primary product. The former is the most liquid market,

as cash is the most liquid asset in the world. The latter is split into two types: hard and soft commodity market. Hard commodities are typically natural resources that must be mined or extracted such as gold and oil, whereas soft commodities are agricultural products or livestock. The last important market to mention is the derivatives market. The value of the products traded on this market, such as options, forwards, futures and swaps, depends on the performance of one or more underlying assets on which each specific derivative product is based. The most common underlying assets for derivatives are stocks, bonds, currencies, commodities, interest rates, and indexes. In the last 40 years, derivatives have become increasingly important in finance, since they play an important role in hedging and speculative operations and they are largely involved in corporate finance strategies.
Not all financial assets are traded on traditional market exchanges. Many trades take place in a decentralized market called over the counter (OTC) market where banks, financial institutions, fund managers, and corporations are the main participants. Once an OTC trade has been agreed by the two parties, they can present it to a central counterparty (CCP) or conclude the trade bilaterally without others being aware of the transaction's terms. Other important characteristics of OTC market are that it is less transparent than traditional exchanges and it is also subject to fewer regulations, exposing its actors to higher risks.

2.2 Introduction to cryptocurrency

Before introducing the concept of Cryptocurrency, it is important to define the main characteristics of fiat money, electronic payment system and blockchain.

2.2.1 Fiat money

Money is an economic unit of value that functions as a recognized medium of exchange for transactional purposes in an economy, which reduce transaction costs. Also, money is commonly referred to as currency, which, in order to carry out its duties in the most efficient way, must be fungible, durable, portable, recognizable, and stable. Initially money was made by coins of precious metals, such as gold and silver. The value of each coin was the same as the amount of precious metal included in the coin itself. Paper money was subsequently introduced, whose value was the worth of a commodity backing it. Later, on 15 of August 1971, with the conclusion of Bretton Woods, the era of commodity backing money ended with the born of fiat money.
Fiat money is government-issued currency that is not backed by a physical commodity, such as gold or silver, but rather by a central authority. Differently from commodity backing money the

value of fiat money is derived from the relationship between supply and demand and the stability of the issuing government. Lot of modern currencies are fiat currencies, including U.S. dollar, the Euro, and other major global currencies. Fiat money is basically cash, a physical object, usually a coin or a banknote. When it is transferred to another individual, its value is also transferred, without the need to involve a third party. Furthermore, no credit or debit relationship arises between the parties involved in the transaction, allowing their anonymity. The advantage of physical money lies in the fact that possession of the value represented by cash is directly attributable to the owner of the physical object, without a central authority needed to keep accounts. Last, any agent can be involved in the cash payment system, without exclusion. Cash, however, also have disadvantages, such as the fact that the counterparties involved in the transaction must be physically present in the same location in order to complete successfully the trade.

The traditional fiat currency requires a centralized system and a trusted figure, such as Government or Central Bank, which must guarantee the money value and manage its supply. This basically means that there are Institutions behind the currency that exist to regulate, emit and control its behaviour. Taking the Euro as an example, besides being the single currency of nineteen countries, there are major institutions that are in part responsible for its well-functioning. One of these is the European Central Bank (ECB). The ECB in particular, is an institution that benefits from some degree of autonomy in regard to the states that have inhered the currency within their borders. These countries have delegated the ECB the task to conduct monetary policy meaning that the main function of the ECB is to either "pump or drain" liquidity from the system in order to stimulate economic growth, price stability and keep inflation low. The tasks and role behind such institution is to keep not only economies within countries stable but to promote stability within the financial system itself. In a broad scope, Central Banks are present within most states of the world, their daily operations might differ from border to border but their main role is always the same, promote stability through monetary policies.

2.2.2 Electronic payment system

An electronic payment system allows to transfer monetary value electronically via cash data files. These types of data files allow to access the advantages related to the physical cash and they are also able to move freely on electronic networks. This form of digital cash can be easily transferred via email or through social media, so that the two parties do not have to be in the same place for the transfer of value. One of the biggest weaknesses of this type of electronic data file is that they can be duplicated without any cost. This can lead to what is called the "double spending problem", i.e. the possibility of duplicating files used as digital cash, not allowing their use as a payment tool. To overcome the problem of double spending, electronic payment systems are based on a centralized authority, generally banks, which verifies the legitimacy of payments and which tracks the status of the various accounts and their monetary value. In this type of system when a buyer initiates a payment by submitting an order, the centralized authority ensures that the buyer has the necessary funds for the transaction and updates the accounts of the two parties involved.

However, a centralized payment system needs reliability and security. Agents must trust the central authority to which they delegate the power to keep books up to date correctly, without taking possession of the money. In addition, centralized systems are vulnerable to hacker attacks and technical failures, so they must ensure that funds are always safe.

2.2.3 Blockchain

Blockchain technology was introduced in 2008 by an individual or a group of developers named "Satoshi Nakamoto", and consists in a digital decentralized distributed ledger that records transactions. Its name originates from "block" and "chain" terms introduced by Satoshi Nakamoto, where transactions are grouped in blocks and chained sequentially with each block linked to the previous one. In this way the whole blockchain represent a complete ledger of all transaction's history.

In a blockchain, each block not only contains the details regarding the transaction and its timestamp, but also the hash value of the previous block and a nonce (random number). This nonce value is used to verify the hash and check the integrity and correctness of the blockchain, when storing transaction details. The hash value is produced using a specific cryptographic hash function, which maps a set of data concerning the transaction, to a fixed-length string composed by numbers and letters. Therefore, any amount of data will always produce an alphanumeric string of the same length, depending on the hash function used. In addition, all transactions entered in a single block are hashed through the Merkle root, which is the result of the hash of all the transaction hashes present in the block. In this way, whatever the number of transactions in a block, the same effort will always be required for the hashing of the block. This cryptographic system allows to prevent any sort of fraudulent change of data within the blocks, since any kind of change would also lead to a change in the respective hash values.

To add a new block to the chain it is necessary that the transactions contained in the block and the block itself are verified by the majority of the nodes that are part of the network, through a

consensus mechanism. This mechanism ensures that all the information that will be added are valid and establishes the rules that nodes must follow to carry out the necessary verifications.
Proof of Work (PoW) is the most popular consensus mechanism, on which the “Hash Cash” algorithm, used by several cryptocurrencies including Bitcoin, is based. With “Hash Cash” algorithm a new block is validated through the "mining process", which rewards the first node that solves a complex mathematical problem, with a newly created coin or fees. Therefore, the probability of verify a new block, and receive the reward, depends on the miner's ability to solve the mathematical problem. This complex problem consists in finding a random value which, combined with the hash value of the transactions and the previous block header, produces a precise given value. When one of the nodes finds a possible solution to the problem, it sends it to the other nodes on the network, who can thus verify it. If the majority of the nodes agree on the result, the block is verified and added to the blockchain. The node that produced the solution is subsequently rewarded. The more time passes, in PoW, the greater the difficulty in mining, leading to a more difficulty for miners in obtaining the reward. Miners are therefore forced to face high costs to own the best hardware in order to win the mining competition and face electricity costs.
Another popular consensus mechanism is the Proof of Stake (PoS), in which the ability to validate a transaction block depends on the amount of cryptocurrency possessed by the miner. Therefore, this protocol rewards miners not based on their effort to solve mathematical problems but based on the stake of the node. The higher the stake the greater the mining power.
Another important feature of blockchain technology is asymmetric cryptography, which allows the user to protect his digital property and transfer encrypted information. All blockchain’s members have two keys, one private and one public. The former, visible only to its owner, allows to access a user’s specific account and is used as a digital signature for transactions. The latter can could be seen by everyone and represents an individual’s account address. To better understand the concept of keys, we can take email as an example. In this case, the public key represents a user's email address, while the private key is the password to access that specific email account. By knowing a user's address, it is possible to send him an email, but to access a specific account and send email from it, it is also necessary to know its password. Similarly, in blockchain, knowing the public key, it is possible to send cryptocurrency to that specific account, but to access it or send cryptocurrency from it, it is necessary to know the relative private key, kept by its specific owner. A user’s public and private keys are kept in. a digital wallet, stored online, referred as “hot storage”, or stored offline, referred as “cold storage”.

Blockchain technology offers numerous advantages over a normal payment system but also has some disadvantages that must be taken into consideration. The main advantage is certainly the decentralized system, which does not require a central authority, and which provides a reliable transaction system without the need for a third party. The distributed system also allows for better fault tolerance and attack resistance. In addition, blockchain allows faster transactions with lower costs than traditional systems, as well as full access to all the network's transaction history, in a totally transparent way for its users. This level of transparency, which confers a higher degree of fairness to accountability mechanism, has never existed before in the financial system.
If we consider the disadvantages instead, the main is certainly the one related to the mining activity. As already described before, the mining challenge to obtain the reward intended for the user who checks a block, requires investing in increasingly advanced hardware and facing high energy costs. Moreover, since mining is highly competitive and there is just one winner for each reward, the work of every other miner is wasted, discouraging miners to invest. Security issues and cyber-attacks are still a problem although the system is distributed. The "51% vulnerability" is one of the main risks of the blockchain network. This problem could occur if a single entity managed to take control of more than 50% of the network's computing power, gaining the power to alter the consensus mechanism and therefore the blockchain itself. Another security problem is linked to the user’s private key. If it is lost, it will no longer be possible to access the related account and the deposited resources will therefore be lost forever. Furthermore, once a transaction has been submitted, it is not possible to cancel it to recover the resources sent. For this reason, if someone were able to steal a user's private key, he could steal the resources deposited on the account simply by sending them to another. The full transparency could also have a negative impact on the user’s privacy and reputation, as everyone could access the whole transaction’s history of the network. The last problem is related to the economic risk, due to the volatile nature of cryptocurrencies, but it will be described better later, when the cryptocurrencies will be presented.

2.2.4 Cryptocurrency market

In the last 30 years have been proposed several alternatives for payment systems. In the 90s, eCash was introduced by DigiCash Inc, which is considered to be the first digital currency, similar to the modern cryptocurrencies. However, it did not overcome the internet bubble of the early 2000s. More modern solutions have been proposed by PayPal, Google and Apple, but all these digital currencies were always based on fiat currencies, and mainly used for online purchases on e-commerce platforms. In a different way, the cryptocurrency presents itself as a real new financial instrument. It is the first and also the most known application of blockchain technology. Taking advantage of this new technology, a distributed payment system has been built and stands on the internet, providing integrity to transactions, without the need for a central authority. This decentralized payment system is used as a direct exchange network for this new form of digital money, and not only as a way to make purchases online.

With more than 3000 coins and a global market capitalization close to $207 Billion, the cryptocurrency market has become an important financial reality. The first coin introduced, as said before, is Bitcoin, with an actual market dominance of 65% (www.coin360.com). Below a short list of the first 10 cryptocurrency by market capitalization.

Rank	Cryptocurrency	Market Cap.	Price	Circulating supply
1	Bitcoin	$180,771,626,581	$9,827.65	18,394,181 BTC
2	Ethereum	$26,992,274,507	$242.71	111,212,767 ETH
3	Tether	$9,243,465,872	$1.01	9,187,991,663 USDT
4	Ripple	$9,030,324,015	$0.20471	44,112,853,111 XRP
5	Bitcoin Cash	$4,717,047,041	$256.00	18,425,900 BCH
6	Bitcoin SV	$3,642,035,930	$197,67	18,424,540 BSV
7	Litecoin	$3,089,928,457	$47,62	64,883,689 LTC
8	Binance Coin	$2,734,278,808	$17.58	155,536,713 BNB
9	EOS	$2,537,063,784	$2,72	933,207,282 EOS
10	Cardano	$2,269,886,636	$0.087549	25,927,070,538 ADA

Table 2.1 - Top 10 cryptocurrency by market cap. at 4/06/2020 (www.coinmarketcap.com)

The website CoinMarketCap.com reports cryptocurrency prices computed as the weighted average of all prices, coming from different exchanges.

In this work, in addition to Bitcoin, four other cryptocurrencies will be analysed, taken from those reported in Table 2.1: Ethereum, Ripple and Litecoin.

- Ethereum (ETH): Introduced in July 30th, 2015 it is the currency of the Ethereum smart contract platform, which allows developers to create the so called ‘DApps’, a sort of decentralized applications, idealized by Vitalik Buterin in 2013. Smart contracts, run on Blockchain and allows executing automatically a transaction, evaluating that the conditions are meet.

- Ripple (XRP) is a ‘Real Time Gross Settlements System’, a currency exchange system that must be validated from independent servers. The currency traded on this network is known as XRP, can be traded in different fiat currencies and transaction time is close to zero. Its high transactions speed allowed XRP to reach a huge success.
- Litecoin (LTC): it is a peer to peer cryptocurrency network, created on the basis of Bitcoin protocol, that utilise a different hashing algorithm. The main objective of Litecoin is to reduce the block certification time from10 minute in order to guarantee faster processing.

Chapter 3

Pricing of financial asset

One of the most important and discussed topics in the field of finance is certainly the possibility of predicting prices' movements. In fact, several empirical tests and researches have been produced to verify if prices follow specific and predictable paths, or if they move in a completely random way. The reason for this great interest is that the predictability of asset prices would allow investors to obtain anomalous returns compared to the normal return of the market. The possibility that prices may or may not be predictable certainly depends on all the factors are believed to determine prices. Traditional and behavioural finance have deeply different opinions on this topic. The main characteristics of these two theories will be presented in this chapter.

3.1 Traditional finance theory

Traditional finance theory uses a series of hypotheses which define the behaviour of investors and the conditions in which they operate, in order to understand the dynamics and model the functioning of the financial markets. More specifically, many models require investors to be risk-averse and make rational choices with the aim of maximizing profits, without being influenced by other factors. These types of models also require an effective arbitrage mechanism, which plays a critical role in determining the prices of the securities, as Miller and Modigliani have pointed out (1958, 1961). In fact, when an arbitrage opportunity arises, which consists of the opportunity to earn by buying and selling the same asset at a higher and lower price respectively, it is essential that this opportunity is immediately exploited by investors. In this way the market will allow the prices to return to the right equilibrium immediately. In the next paragraphs of this chapter some pricing models related to traditional finance theory will be presented, together with the Efficient Market Hypothesis.

3.1.1 Equilibrium asset pricing model

3.1.1.1 Capital Asset Pricing Model

The best-known method for asset pricing is the Capital Asset Pricing Model (CAPM) elaborated by Sharpe, Lintner, and Mossin (1964-1966). This model is based on the Modern Portfolio Theory presented in a 1952 article by Markowitz. CAPM's main assumptions include the presence of an ideal market, in which there are no transaction fees, taxes, inflation and short selling restrictions. In addition, investors aim to maximize profit by making rational choices, being able to access all available information. For these reasons, they will invest in a combination of a riskless security and the same well-diversified and efficient portfolio of risky stocks, i.e. the market portfolio. Sharpe, Lintner and Mossin suggest that if all the investors have a well-diversified portfolio, deleting all specific risks, and they act rationally in order to maximize their return, there must be an increasing relationship between the expected return of each asset and its systematic risk, defined as beta. The linear relationship is defined as:

$$E(r_i) = r_f + \beta_i(E(r_m)-r_f)$$

Where:

- $E(r_i)$: expected return of asset i
- r_f: risk free rate
- $E(r_m)$: expected return of the market portfolio (portfolio whose expected return is equal to the expected return of the makret as a whole)
- β_i: sensitivity of asset I's return to the return of the market portfolio

The CAPM can be illustrated through the Security Market Line (SML):

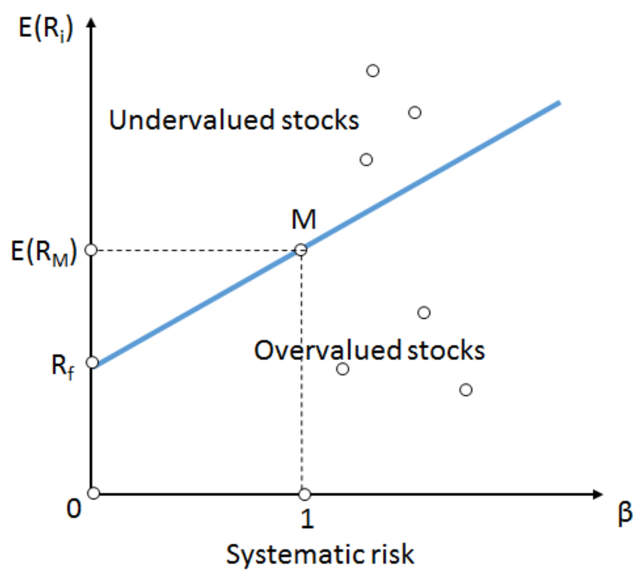


Figure 3.1 – Security Market Line (SML) – [source: wikipedia]

According to the CAPM, all assets, and portfolios of assets, must lie along the SML. If any asset lies above or below the line then it would be considered either overvalued or undervalued, and the arbitrage mechanism would take place until the asset converges on the line. Therefore, following the CAPM, each asset always carries its correct fundamental value, and the difference in the expected returns of the assets depends only on their beta. In particular, if an asset is riskier than the market, it will have a beta greater than 1, as investors expect a higher return. Vice versa, a less risky asset than the market will have a beta lower than 1, providing a smaller return.

3.1.1.2 Arbitrage Pricing Theory and Three-Factor Model

Even if the CAPM has met a great success among traditional finance supporters, some researchers have proposed new approaches for the financial asset pricing. In 1976, Ross formulated the Arbitrage Pricing Theory (APT), which asserts that the expected return of a financial asset is related to one or more indices with a linear relationship and that there is a specific sensitivity between the asset and each of these indices. This linear relationship is defined as:

$$E(r_i) = a_i + b_{i1}I_{i1} + b_{i2}I_{i2} + b_{i3}I_{i3} + ... + b_{ij}I_{ij}$$

Where:

- $E(r_i)$: expected return of asset i
- a_i: expected return of asset i if all indices have a value of zero
- I_{ij}: value of the jth index that impacts the return of stock i
- b_{ij}: sensitivity of stock i's return to the jth index

In the model, the value of the indices is always the same for all the assets considered, while the sensitivity change for each asset. Therefore, as a result of the previously defined arbitrage system, all the assets with the same sensitivities to the indices will have the same expected return. As seen with the CAPM's Security Market Line, the APT can be graphically illustrated by a n-dimensional plane, with n equal to the number of indices J. All portfolios or group of assets, that lie above or below the plane, will immediately converge to it thanks to the arbitrage mechanism. The big disadvantage of this model is that the indices are not defined by the theory, making the model useless for the practical case.

In the absence of a well-defined indices, several researchers and professionals, including Sharpe (1982), Chen, Roll, and Ross (1986), and Fama and French (1993), have proposed several sets of indices. The Fama and French model presented in 1993 was particularly successful. Starting from the study of the stocks of NYSE, AMEX and NASDAQ in the period from 1963 to 1990, Fama and French have shown that the expected return of a security is explained by three factors:

1. The excess of return of the market over the risk-free-rate
2. A size factor (SMB)
3. Book-to-market factor (HML)

The book-to-market factor is used to compute a company's value by comparing its book value to its market value. The ratio is calculated dividing the common shareholders' equity by the firm market capitalization. If market value of a company is higher than is book value, the firm is considered overvalued. Vice versa if the book value is higher than the market value the company is undervalued.
The three-factor model proposed by Fama and French can be explained by the following equation:

$$E(r_i) = r_f + \beta_i(E(r_m)\text{-}r_f) + s_iE(SMB) + h_iE(HML)$$

Where:

- $E(r_i)$: expected return pof stock i
- r_f: risk free rate
- $E(r_m)$: expected return of the market portfolio
- E(SMB): expected difference in the return of a portfolio of small stocks and a portfolio of big stocks (SMB = small minus big)
- E(HML): expected difference in the return of a portfolio of high book-to-market stocks and a portfolio of low book-to-market stocks (HML = high minus low)
- β_i, s_i and h_i = sensitivity of stock i's return to the return of the market portfolio, the size factor and the book-to-market factor, respectively

In their model Fama and French state that not only beta should be considered a proxy for risk of an asset, but also the dimension (i.e. market capitalization) and book-to-market value of the firm. The two researchers say that the risk related to small firms, which have a greater book to market value, is significantly higher than the risk of companies which are bigger and have a lower book to market value. Excluding this, the concept of the Three Factor Model is the same of the CAPM.

3.1.2 The efficient market hypothesis

The theory known as the Efficient Market Hypothesis (EMH) was developed in the1960's by Fama. Differently from the previous models, the EMH is not a model for determining the price of stocks, but only a hypothesis that states that the security prices reflect the fundamental values at all times.

The most important features of an efficient market are:

- Asset prices answer quickly to new information available
- At any time, there is a linear relationship between expected return and risk because the expected returns are related only to changes in the risk-free rate and in risk premiums
- It is impossible to identify profitable trading strategies because is impossible to recognize investments that will provide profit or not in the future
- Different investment performance among investors are entirely due to chance

Fama argues the market pricing is efficient, due to the large number of investors who are involved and the fact that they are well updated about news and rational, continuously involved in the research of profitable trading opportunities. In order to have a fully efficient market, the cost for obtaining information and trading securities must be zero. Of course, this is not the case of the real world. For this reason, Fama (1970) suggested three different degrees of market efficiency:

1. Weak efficient market, in which all historical information is incorporated by current prices
2. Semi-strong efficient market, in which all publicly available information, not only historical information, is incorporated into current prices
3. Strong efficient market, in which both public information and insider information are incorporated in current prices

It is easy to understand that under any degree of efficiency proposed by Fama it is not possible for an investor to obtain abnormal returns, even after extensive studies and analysis of price movements over time. Moreover, unlike previous models, EHM does not believe that all investors are rational, but that the market is rational. This means that the irrational actions taken by some investors are considered totally random and that their effect on prices will cancel each other out causing a null total effect on the market. If this does not happen, according to EHM, these errors will be corrected by the arbitrageurs. The result is therefore that prices reflect only the fundamental values and that they do not show systematic deviations from their efficient value.

3.1.3 Implication of traditional finance

One of the key points of all traditional finance models is that there are specific factors that determine the risk of an asset, thus defining its price. Any deviations from this equilibrium price is immediately cancelled by well-informed investors who act as rational arbitrageurs. Also, as prices reflect the new information available quickly and accurately, the EMH claims that assets are always traded at their fundamental values. According to traditional finance theory, due to arbitrage, there are no securities that are traded at prices above or below their equilibrium price. For this reason, it is useless try to identify specific trading strategies capable of generating abnormal returns. This because prices movement is completely random, making it impossible to predict future asset prices trend. The forecast of price movements, using historical data taken from the past, would lead to the formulation of trading strategies that produce abnormal profits, only if the traditional finance theory is incorrect in explaining the dynamics in which the market operates. Starting from this possibility, the following section examines a more recent financial theory, known as behavioural finance.

3.2 Behavioural finance theory

The majority of models developed thanks to traditional finance theory is based on several assumptions, which often seems to be unrealistic. Moreover, in the 1980s, a large number of researchers began to experience a series of empirical results, incompatible with the price equilibrium and efficient market models developed before. These results include several effects such as the momentum, the reversal, the size and the January effect that were considered only anomalies by traditional finance. Anyway, the persistence of these anomalies, and the emergence of new ones, has led scholars to wonder if the models deriving from traditional finance are able to understand and describe the market dynamics and the movement of financial asset prices efficiently. Trying to answer to this issue, a new theory known as behavioural finance was formulated in the 1980s. This new theory is based on two fundamental pillars, the investor's psychology and the limits of arbitrage.

3.2.1 Investor psychology features

The most important innovation of behavioural finance is to incorporate several concepts and studies from social sciences and psychology into the financial theory. Unlike traditional finance, that idealizes the investor as a rational entity, behavioural finance takes into account the thoughts, emotions and actions of real people. It is therefore based on the idea that investors do not always act rationally, and that their behaviours can influence the entire market, making it irrational. In particular, it is believed that irrationality derives from psychological biases, which influences the methodology used by people to create their expectations and make decisions. All these biases lead to cognitive errors, influencing the way people think, therefore one of the main aspects studied by behavioural finance is the influence of these biases on the investor and the whole market.

One of these biases is given by the risk preferences of the investors, which differ from those presented by the traditional theory. The most recognized model for risk preferences is the prospect theory, which states that investors, instead of being risk-averse in all situations, are risk-averse over gains, and risk-seeking in relation to losses. This can be summarized in the statement that people dislike more losing than they like winning, or that losses and gains are valued differently. For example, for some individuals, the pain from losing $1,000 could only be compensated by the pleasure of earning $ 2,000, not by a gain of only $1,000 to recover the loss.

Differently, other biases could push investors to fall in error by making non-rational choices, as they are unable to interpret and exploit the large amount of information available. For example, some investors may be easily influenced by decisions made by others, which can be irrational as a result of some biases. This decision imitation could have a great influence on the market as a whole. To better explain the dynimics among investors, behavioural finance theory uses the concept of herd behaviour, which states that people, instead of following their own idea and information, are inclined to imitate the behaviour of others. Research has shown that herd behaviour is more pronounced when information is poor and when complexity is high. Under these conditions, investors are more likely to be influenced by others.

Other examples of biases studied by behavioural finance are the disposition bias, conformation bias and experimental bias. Disposition bias refers to when investors tend to close their gain positions early, in order to make gains quickly, and hold their loss positions for a longer time, to try to recover potential losses. This happen because investors are reluctant to admit when they made an investment mistake.

Confirmation bias is the tendency of people to pay attention and accept information confirming their convictions, on which they based their investment strategy.
The experimental bias occurs when investors' memory of a recent event leads them to believe that the event can occur again. For example, after the 2008 crisis investor were afraid that stock market will continue to drop, but it recovered all the value in the years following the market crash.
Behavioural finance therefore contradicts traditional finance theory by stating that investors often act irrationally, thereby causing prices to deviate from their fundamental values. These price deviations can persist even for long periods due to limits in the arbitrage mechanism which should instead guarantee a rapid return to equilibrium prices ensuring market efficiency.

3.2.2 The limits of arbitrage

As previously presented, the theory of traditional finance recognizes the possibility of a deviation of prices from their equilibrium value. However, it claims that there are arbitrageurs at all times who are sufficiently informed to recognize and exploit the profit opportunities that have arisen. Therefore, according to the theory of traditional finance, even if deviations from the fundamental values occur, they will exist for a short time period because they are corrected by the action of the arbitrageurs, making their effect on the market insignificant. The idea that erroneous prices can only exist temporarily is opposed by behavioural finance supporters, who say that deviations can persist for prolonged periods of time due to some limitations of the arbitrage mechanism. The fundamental concept on which this hypothesis is based can be traced back to the assumption that arbitrage is risk free. In a 1990 article, De Long, Shleifer and Waldmann argue that arbitrage opportunities may not always be risk free and that the risk associated with arbitrage trading could discourage investors from undertaking this operation, not allowing price correction. More precisely, De Long introduces a new risk term known as noise trader risk. This new risk is due to the fact that investors can make trading decisions based on incorrect or misleading information (noise) which have instead been interpreted as valid and reliable, influencing the whole market. For example, if noise traders have been bullish on a stock, raising its price beyond the fundamental value, according to traditional finance, informed investors should short sell the stock, returning the stock price to its fundamental value. The noise trader risk is the risk that noise traders can become even more bullish, discouraging rational, risk-averse investors from opening a short position on the stock. In conclusion, according to behavioural finance, the irrationality of investors causes incorrect prices, while the limits of arbitrage allow to pursue incorrect prices.

3.2.3 Implications of the behavioural finance theory

In contrast to traditional finance theory, behavioural finance describes investor behaviour as one of the main causes that determine asset prices. Furthermore, it states that investor behaviour may not always be rational due to psychological biases and non-rational risk preferences. All these factors can have a huge impact on the entire market. Moreover, incorrect assessments of non-rational investors will have long-lasting effects on the market, due to the noise trader risk that discourages the activation of the arbitration mechanism. Of particular interest, in the continuation of this thesis, is the fact that irrational investors and the limits of arbitrage can lead to market inefficiency, whereby asset do not necessarily carry their fundamental value or follow a random walk, as argued by traditional finance theory. Differently, the assets could be priced using some predictable investment patterns, which can be exploited by the investors. This means that the implications of behavioural finance could lead to predictable asset prices, allowing for the identification of trading strategies such as momentum strategy.

Chapter 4

Momentum effect

As previously analysed, various phenomena, which are incompatible with traditional finance theory, have been observed in the financial markets. Among these phenomena are the momentum effect and the mean reversion effect. In short, momentum effect refers to the positive autocorrelation of prices or the tendency for rising asset prices to rise further and falling prices to keep falling. On the contrary, the reversion effect refers to the phenomenon whereby asset prices show a negative autocorrelation, and therefore after a certain period of deviation they revert and move back to their fundamental values. Both of these two phenomena clearly contradict Efficient Market Hypothesis and the Random Walk Model since they indicate that it is possible to predict the direction in which asset prices will move in the future, making it possible to identify profitable trading strategies. Furthermore, the two effects seem to contradict each other. For example, a strategy based on momentum effect consist in buy past winners and short sell past losers. On the contrary, a strategy based on the mean reversion effect consist in buy past losers and short sell past winners. Academic research focused mainly on contrarian strategies, developed in the 1980s. For example, De Bondt and Thaler (1985) have shown that contrarian strategies, which buy assets that have had poor returns in the previous 3-5 years, and sell assets who have achieved good results in the same period, obtain anomalous returns during a holding period ranging from 3 to 5 years. Similarly, Jedadeesh (1990) and Lehman (1990) have documented that contrary strategies, that select assets based on their performance in the previous weeks, generate abnormal returns due to short-term market reversals. Although contrarian strategies are widely recognized by academic literature, some investigators claim that relative strength is a valid selecting criterion. Mutual funds, for example, tend to buy securities that have increased in price compared to the previous quarter, thus taking advantage of momentum strategies. The following chapter is going to present the momentum strategy focusing on the main characteristics and its use for trading various traditional financial assets and cryptocurrencies.

4.1 Commonly used mythology

Momentum investing basically involves investments based on past asset price trends. More specifically, recent asset price trends are expected to be maintained in the near future.

Therefore, following this investment strategy an investor should buy assets that have recently had high returns, and short sell assets that have had low returns, in order to outperform the market. The most commonly used method for testing the profitability of a momentum strategy is based on the pioneering work of Jegadeesh and Titman (1993). The methodology applied to stocks works as follows:

at the beginning of each month of the decided sampling period, stocks are ranked in ascending order based on their returns over the past J months, where J is the formation period (3,6,9 or 12 months). Based on this ranking, the stocks are divided into portfolios, all composed of the same number of stocks, and in which the quantities of the stocks contained are equally weighted. The portfolio that contains the stocks with the highest past returns is called the winner portfolio, the one containing the stocks with the lowest returns. Losing portfolio. In each month t, the two portfolios are purchased and held for a holding period of K months (3,6,9 or 12 months). Also, the opened position in month t-K is closed. Therefore, each month the strategy holds a series of selected portfolios in the current month and previous K-1 months. The monthly return of month K is calculated as a weighted average of the returns of the portfolios in the current month and in the previous K-1 months. The monthly return is calculated for both portfolio types, winner and loser. At the end of the sampling period, the performance of the momentum strategy is calculated as the average monthly return of the winning portfolio minus the average monthly return of the losing portfolio, during the sampling period. The return on the strategy is defined as the return of the zero-cost portfolio, since a strategy that short-sells the loser portfolio and buys the winner portfolio potentially present no cost for the investor, if no transaction fees are considered. Finally, it is possible to say that the momentum strategy is profitable if the yield of the momentum, or of the portfolio at zero cost, is positive and statistically positive. In addition, Jegadeesh (1990) and Lehman (1990) suggest skipping a week, or sometimes a few months, between training and holding periods, to avoid bid-ask spreads and run into short-term reversal effects.

4.2 Empirical findings of momentum strategies

The following present the results of a series of studies on momentum strategies applied to different markets. The focus of this review is on the degree and robustness of the price momentum.

4.2.1 Empirical studies of the American stock market

The first academic paper documenting that momentum strategies are capable of generating significantly positive earnings for holding periods ranging from 3 months to 12 months was published by Jegadeesh and Titman in 1993. In this paper the two researchers analyse the stocks of the NYSE and AMEX during a sampling period from 1965 to 1989 and find that the returns of 32 momentum strategies examined are positive. In general, it appears that strategies with long training periods of 9 or 12 months and short holding periods of 2 or 3 months have slightly better returns compared to the other strategies using longer periods.

Starting from the studies of Jegadeesh and Titman in 1998 Conrad and Kaul analysed momentum strategies with equal duration of training and period of holding period. Their study analyses periods ranging from 1 week to 36 months, which therefore also includes shorter time windows than previous researches. The studies carried out by Conrad and Kaul confirm the momentum effect by documenting profits up to the 18-month strategy.

The 6-months / 6-months with no time lag between formation and holding periods produced by the Jegadeesh and Titman study is considered the most representative of their research, with an average monthly return of 0.95%. Based on this strategy, the two researchers verified the effect of risk and one-way transaction cost equal to 0.5% per transaction, arriving to calculate a return of 9.29% per year. Therefore, the momentum strategies seem profitable even after taking into account the risk and transaction costs, thus getting closer to the real case. This fact has also been confirmed by the studies of Korajczyk and Sadka (2004). Korajczyk and Sadka also found that value-weighted strategies work better when taking costs into account than equally weighted ones, since in a value-weighted portfolio they attribute greater weight to larger and more liquid stocks, which are cheaper to negotiate and therefore they have lower transaction costs.

Subsequently, Jegadeesh and Titman tested further the profitability of momentum strategies by using subsets of firms based on their size. They found out that although returns appear to be related to the size of the company and in particular to their beta, all returns from individual stocks within the strategies are positive. Therefore, the profitability of momentum strategies does not appear to be limited to any particular subset of stocks.

Another important result achieved by Jegadeesh and Titman was that the momentum strategies do not appear to be limited to any sub-period. In their research Jegadeesh and Titman examine the zero-cost portfolio returns for different strategies in each 5-year subset of the sampling period, running from 1965 until 1989. In all cases a positive return is noticed, except in the 5-year period from 1975 to 1979. The main cause for the negative return of this sub-period is due to the January returns of small enterprises. Therefore, if implemented only on medium and small enterprises, or excluding the month of January, momentum strategies show positive returns on all sub-periods of 5 years. During these analysis Jegadeesh and Titman observed a strong January effect. By examining monthly returns, the two researchers found out that the momentum strategy loses 6.86% on average each January, and gains positive returns in all other months, with an average return of 1.66% per month. Similar results were found by Grundy and Martin (2001), who, by analysing the NYSE and AMEX stocks, in the period from 1926 to 1995, using a 6-month / 1-month momentum strategy, obtained an average monthly return of -5.85% in January and 1.01% in the other months. The negative returns of January also correspond to the results of De Bondt and Thaler (1985), who believe that the profitability of the reverse strategies is particularly high in the months of January.

Trying to evaluate whether the observed price pattern is persistent over time, Jegadeesh and Titman monitored the average returns of the zero-costs portfolio in the 36 months following the formation date. Excluding the first month, the average return on the zero-cists portfolio is positive in each month of the first year, but negative in each month of the second year and in the first half of the third. Thereafter, the yield is zero. Therefore, the cumulative return of the portfolio reaches a maximum of 9.51% of positive return at the end of the first year and decreases to 4.06% at the end of the 36 months observed, indicating that the price trend is not permanent. Consistently with the results of Jegadeesh and Titman, Lee and Swaminathan (2000), have observed a modest reversal of momentum earnings in years 2 and 3, but again not statistically significant negative returns. By extending their study to years 4 and 5, however, a model of price reversal emerges. In the years 4 and 5 in fact all the returns of zero-cost portfolios are negative, and it is observed that the effect of the inversion increases as time passes. Lee and Swaminathan are therefore the first to document that the momentum in stock prices reverses over longer horizons.

Subsequently, in 2001, Jegadeesh and Titman will extend their study of momentum strategies to the sampling period from 1990 to 1998, confirming their profitability also in this second period.

4.2.2 Empirical studies on emerging markets

Rouwenhorst (1999) is one of the first to study the momentum effect on emerging markets, which are particularly attractive because of their relative isolation from the more developed markets of other countries. In his research, Rouwenhorst examines a sample of 1705 companies from 20 emerging countries, in the period from 1982 to 1997, using a 6-month / 6-month strategy, which at the beginning of each month ranks stocks into three portfolios: top 30 %, middle 40% and bottom 30%. The results show that past winners have better returns than past losers in 17 of the 20 countries, with average monthly returns ranging from -0.79% of Argentina to 2.09% of Colombia, with an average monthly return of all 20 markets of 0.39%. In general, although Rouwenhorst's results indicate a lower momentum effect in emerging markets compared to developed markets, they still confirm the existence of a momentum effect. In particular, investors operating in emerging markets have poor information, therefore they will be unlikely to be able to operate in an informed and rational way. This particular condition, as already described by behavioural finance, can be the cause of the momentum effect of emerging markets.

4.2.3 Momentum effect after price overreaction

Several empirical studies and researches have reported evidence of price overreactions. Overreaction in finance indicate a period in which asset prices tend to rise or fall significantly, often due to psychological reasons rather than fundamentals. De Bondt and Thaler (1985) develop an overreaction hypothesis which try interpreting price movements caused by abnormal price fluctuation. DeBondt and Thaler (1985 and 1987) suggest that investors tend to overreact to new information. Also, they provide evidence of price reversals after stocks have exhibited abnormal positive or negative returns. In other words, losers tend to rise, and winners tend to decline in the following periods. Subsequently, new studies were produced concerning abnormal price fluctuations and patterns (Madura and Richie, 2004; Mynhardt and Plastun, 2013; Ferri and Min, 1996); trading strategies able to make profits based on overreactions (Caporale and Plastun, 2019); the influence of price overreactions on the investor behaviour (Savor, 2012). According to the price overreaction hypothesis there is a price reversal after anomalous price fluctuations.

Several studies have described this effect on different asset classes such as the US stock market (De Bondt, Thaler and Jegadeesh, 1993; Ferri and Min, 1996), other stock markets (Lobe and Rieks, 2011; Mynhardt and Plastun, 2013), FOREX (Caporale et al., 2018), option markets (Poteshman, 2001) and commodity markets (Cutler et al., 1991), and the majority of them have found evidence of price reversals after overreactions. Differently, a few researches have detected instead momentum effects after one day of abnormal returns (Cox and Peterson, 1994). Cox and Peterson find that negative returns occur after a large one-day decline. This evidence contrasts the overreaction hypothesis of DeBondt and Thaler (1985).

4.2.3.1 Momentum effect in the cryptocurrency market after price overreaction

The cryptocurrency market is a particularly new and relatively unexplored case of market extremely vulnerable to overreactions, given its high volatility compared to the traditional markets such as FOREX, commodity and stock etc. Recent studies have analysed its efficiency (Bartos, 2015; Urquhart, 2016), long-memory properties and persistence in price (Bariviera et al., 2017;), the existence of price bubbles (Corbet et al, 2018), its competitiveness (Halaburda and Gandal, 2014), the issue of price predictability (Bouri et al, 2018; Caporale et al., 2019) and the presence of anomalies (Kurihara and Fukushima, 2017; Caporale and Plastun, 2018).

The possibility that there is a momentum effect in the cryptocurrency market is due to its affinity with emerging markets, which are difficult to reach and whose information is often scarce or difficult to interpret. Since large financial institutions do not have the authorization or interest to operate on the cryptocurrency market, small investors often have to access it directly, by creating a wallet and using an exchange. Although these have developed a lot in recent years, becoming more user-friendly, they still remain a strong obstacle to accessing the market. A second huge problem is given by the type of asset being traded, the cryptocurrency, which is much more complex to understand than traditional assets, such as stocks, commodities and forex. It therefore follows that investors are generally small players or individuals, attracted by the high volatility of the cryptocurrency market and by the possibility of speculation, which make decisions often driven more by common sentiment, than by reasoning based on facts and concrete data.

Anyway, there is a small number of studies focusing on momentum and overreactions in the cryptos market. The research of Chevapatrakul and Mascia (2019), based on the quantile autoregressive model, reveals that days with deeply negative returns are often followed by periods again characterised by negative returns and that abnormal positive weekly returns will be followed by an increase in prices More specifically, investors seem to overreact when daily returns are in the lower quantile of the distribution and when weekly returns are in the upper quantile of the distribution. The two researchers' interpretation of the first is that investors are quick to exit the market on days of negative feelings when prices drop. Otherwise for the second finding, the results indicate an excessive reaction of investors to favourable news, during the weeks of positive sentiment when prices are rising. At the monthly frequency, no evidence of momentum was found, thus suggesting that the cryptocurrency market has much faster momentum dynamics compared to traditional asset markets, such as the stocks market.

In their paper of 2019 Caporale and Plastun have revealed the presence of price patterns after overreactions. Also, they have analysed the momentum effect in the crypto market during the overreaction day and the day after. The researchers find that, after an overreaction, the price moves are higher than in normal days and for these reasons, they support the thesis that a trading strategy based on the momentum effect after overreactions is profitable. In the research, hourly data of BTC, ETH, XRP and LTC against USD rates over the period 01.01.2017-01.09.2019 are investigated using several statistical methods and trading simulations. The results show that hourly returns during day of positive/negative overreactions are significantly higher/lower than hourly return during the average positive/negative day.
Moreover, anomalous days can be recognized before the day end. In fact, the prices trend is to follow the direction of the overreaction until the end of the day, making arise the momentum effect. This effect, that allow potential profit during the overreaction day, is also detected the following day. Instead, in the case of positive overreactions on Bitcoin and negative overreactions on Ethereum, a reversal effect arises. The Caporale and Plastun findings are of interest to researcher and investors, willing to maximize their profits, and are the starting point of these thesis research.
Specifically, this thesis work will attempt to verify the results proposed by Caporale and Plastun, tests their hypotheses on other cryptocurrencies of lower market capitalization and develop an effective trading system, able to produce profits systematically.

Chapter 5

Heuristic trading strategy

The objective of this chapter is to verify if the cryptocurrency market is subject to a momentum effect and if this implies the possibility of profit for speculators. First, there will be a test of the results reported by Caporale and Plastun (2019) and then the implementation of a trading strategy, operating on a set of cryptocurrencies, able to exploit the momentum effect to generate profits.

5.1 Hypothesis

In their paper Caporale and Plastun examine if there is a momentum effect after a day of abnormal returns in the cryptomarket. For this purpose, 3 hypotheses of are tested on the Bitcoin, Ethereum, Ripple and Litecoin, over the period between 01.01.2017 and 01.09.2019. The hypothesis tested are the following:

- H1: the hourly returns intraday behaviour is different on abnormal returns days compared to normal returns days
- H2: on overreaction days there is a momentum effect
- H3: on the day after an overreaction day there is a momentum effect

5.1.1 Caporale and Plastun results overview

The methods used by the two researchers for their study include several statistical methods and trading simulations. The findings of their research show that the hourly returns of the days with abnormal overall returns are particularly higher than those observed on average days. Also, prices trends follow the same direction of the overreaction until the end of the day. This behaviour is explained by the presence of a momentum effect on that specific day, giving the arise of exploitable profit opportunities. The momentum effect, together with profit opportunities, is also observed on the following day but, in the case of positive overreactions on Bitcoin and negative overreactions on Ethereum, a reversal effect arises. Moreover, overreactions can usually be identified before the end of the day by checking specific timing indicators. As mentioned before, these finding are going to be tested in this chapter.

5.2 Hypothesis verification

5.2.1 Dataset composition

Before exposing the methodology utilized to verify the hypotheses, it is necessary to present the data that have been used. The sample utilised presents both daily and hourly data of the following cryptocurrencies: Bitcoin, Ethereum, Ripple and Litecoin. These are four of the most known cryptocurrencies with high market capitalisation.

The datasets utilised are composed by data provided by one of the most-known cryptocurrency exchanges and trading platform, www.kraken.com, and were downloaded from www.cryptodatadownload.com in CSV format. For each cryptocurrency, are available data of two different granularity:

- Hourly (from 1/1/2018 to 27/05/2020)
- Daily (from 1/1/2017 to 27/05/2020)

Each dataset, both hourly and daily, are composed by the following features:

Timestamp	*Open*	*High*	*Low*	*Close*	*Volume Crypto*	*Volume USD*

5.2.2 Normal and overreaction day definition

In order to verify the hypotheses, it is necessary to separate each day into two distintc categories, normal and overreaction day. To do this, the daily return and standard deviation have been calculated.

Daily return

$$R_i = \left(\frac{Close_i}{Open_i} - 1\right) * \ 100\%$$

Where:

- R_i: returns on the i-th day in %
- $Open_i$: open price on the i-th day
- $Close_i$: close price on the i-th day

Average daily returns

$$R_n = \sum_{i=1}^{n} \frac{R_i}{n}$$

Where:

- R_n: average daily returns for period n
- R_i: returns on the i-th day
- n: number of days in the period

Standard deviation

$$\delta_n = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(R_i - R_n)^2}$$

Where:

- δn: standard deviation for period n
- R_i: returns on the i-th day
- R_n: average daily returns for period n
- n: number of days in the period

The returns calculated using the previous formula are separated into the positive and negative overreactions datasets, in order to test the price behaviour in these two different situations.

The positive overreactions are identified using the following returns indicator:

$$R_i > (R_n + k * \delta_n)$$

The negative overreactions are identified using the following returns indicator:

$$R_i < (R_n - k * \delta_n)$$

The parameter k represents the number of standard deviations, specific for each cryptocurrency, used to identify the overreaction.

5.2.3 Verification methodology

To verify the three hypotheses the behaviours of the overreaction days found in the period from 01/01/2018 to 27/05/2020 has been analysed. In this first phase it has been decided to use a value of k equals to 0 for each cryptocurrency. Therefore, are considered overreaction all the days that produce a daily return greater than the average return of the positive days or less than the average return of the negative days. In this way, each day is divided into three categories, according to its specific total return. This division is explained in the following graph:

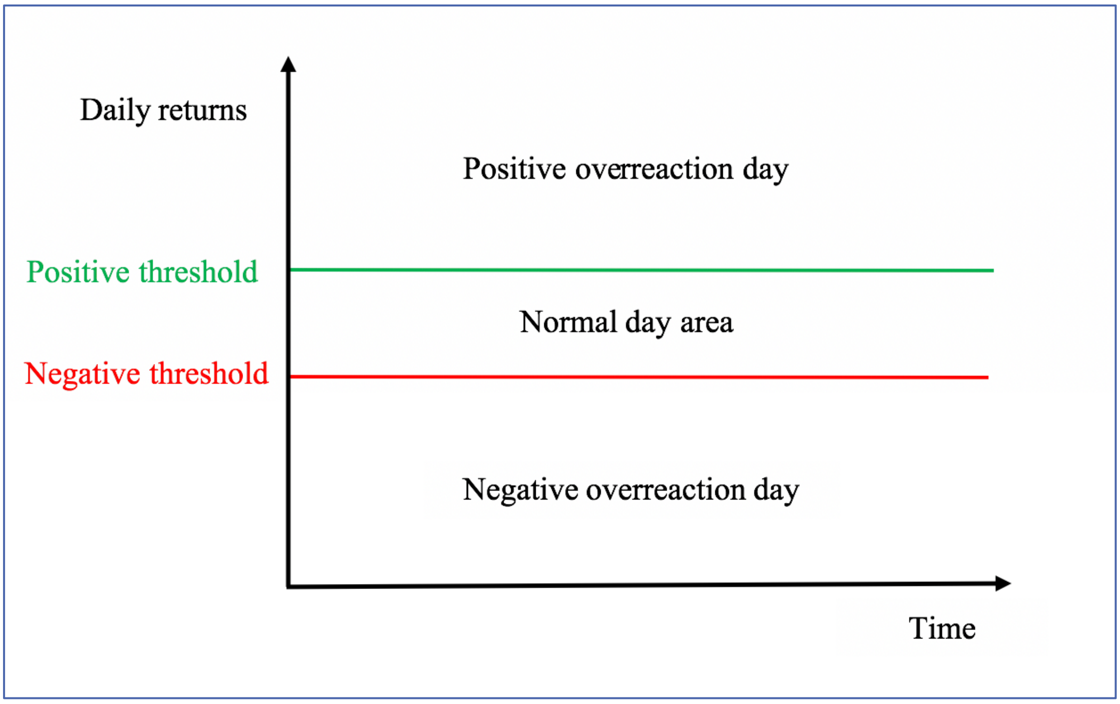


Figure 5.1 - Representation of the overreaction day and normal day division

If the daily return of one day is above / below the positive / negative threshold, then the day falls into the group of positive / negative overreaction days. If, on the other hand, the value of the daily return is between the two thresholds, then the day is considered a normal day. In table 5.1, are reported the result of the division for each of the four cryptocurrencies taken into consideration, with the number of the days belonging to each class.

Cryptocurrency	**Positive overreaction days**	**Negative overreaction days**	**Positive normal days**	**Negative normal days**	**Total day analysed**
Bitcoin	154	153	289	270	866
Ethereum	158	149	263	296	866
Ripple	132	169	273	292	866
Litecoin	141	170	258	297	866

Table 5.1 – Days classification by daily return

To understand whether the intraday behaviour of the overreaction days is different from the normal days, as supported by the H1 hypothesis, and whether there is a momentum effect during the overreaction days, as told by the H2 hypothesis, the hourly returns have been checked analysing the graphs shown in Appendix A, which present the average hourly returns of the overreaction days and the normal days in comparison. As can be seen from the Appendix A graphs, the average hourly performances of the overreaction days are significantly different from those of the normal days, for all the four cryptocurrencies taken in consideration. Normal days have small hourly returns, both positive and negative. The average hourly returns of overreaction days instead tend to be bigger, about three times higher than those of normal days, and all in the same direction. In fact, on positive overreaction days the average hourly returns are all positive, while on negative overreaction days the average hourly returns are all negative. From the analysis of these graphs it is therefore possible to deduce that the behaviour on overreaction days is much more pronounced and that it persists throughout the whole day, verifying hypothesis H1. To better understand if it is actually present a momentum effect during the overreaction days and verify H2, can be also useful look at the daily average returns of the overreaction days, and confront them with the thresholds used to classify the days into normal and abnormal returns days.

The following table shows the average returns of all positive and negative days, used as thresholds, and the average returns of normal and overreaction days.

Crypto	**Pos. days**	**Neg. days**	**Pos. over. days**	**Neg. over. days**	**Pos. nor. days**	**Neg. nor. days**
Bitcoin	2.80%	-2,85%	6.03%	-6.00%	1.08%	-1.07%
Ethereum	3.78%	-3.60%	7.52%	-7.67%	1.53%	-1.54%
Ripple	3.80%	-3.60%	8.45%	-7.30%	1.55%	-1.44%
Litecoin	4.13%	-3.63%	8.25%	-7.23%	1.88%	-1.57%

Table 5.2 - Average daily return (all days, overreaction days and normal days both positive and negative)

As can be seen by looking at the data shown in table 5.2, there is a clear difference between the average return on normal days and that on overreaction days. The latter in fact have an average daily return about five times greater than that on normal days, both positive and negative. This data confirms what had already been seen in the charts with the hourly returns data of Appendix A, further validating the hypothesis H1.

Moreover, it can be noted that the average return of the overreaction days is much greater than the threshold values chosen to define the overreactions. This means that an overreaction day tends to have a much more pronounced trend than the average day. This is due to a further increase / decrease in prices during the overreaction day compared to the positive / negative threshold value. Specifically, this result can be explained by a momentum effect. Taking Bitcoin as an example, all days with a daily return greater than the threshold value of 2.80% are considered positive overreaction days. The average return of these positive overreaction days is 6.03%. The difference between these two values of 6.03% - 2.80% = 3.23% represents the further increase in the price of Bitcoin due to the momentum effect. If a positive overreaction day is identified, it would therefore be possible to exploit the momentum for speculative activities. The data of table 5.2 show that there is this speculative chance for all four cryptocurrencies analysed, both for positive and negative overreaction days. The possibility of exploiting these results to create profits will be described later in this chapter when the trading strategy is presented.

To verify if there is a momentum effect also on the day after the overreaction, as supported by hypothesis H2, the average hourly returns, taken from the days following the days with normal and abnormal returns, are compared. As can be deduced from the graphs in Appendix B, the average hourly returns of the days following an overreaction tend to be greater than those following normal days, confirming the anomalous trend found in Appendix A. Furthermore, the average hourly returns are both positive and negative, without a specific trend. These evidences can be found in all cryptocurrencies, after both positive and negative overreaction. To verify the presence of momentum and the possibility of profit, it is therefore necessary to better analyse the results of the days following an overreaction.

Overreaction type	# of pos. ov. days	# of neg. ov. days	# of pos. norm. days	# of neg. norm. days	Tot.
Positive	27	33	51	42	153
Negative	46	30	49	28	153

Table 5.3 - Classification of the days following overreaction – Bitcoin

Overreaction type	# of pos. ov. days	# of neg. ov. days	# of pos. norm. days	# of neg. norm. days	Tot.
Positive	26	31	36	65	158
Negative	36	30	49	34	149

Table 5.4 - Classification of the days following overreaction – Ethereum

Overreaction type	# of pos. ov. days	# of neg. ov. days	# of pos. norm. days	# of neg. norm. days	Tot.
Positive	24	46	21	41	132
Negative	43	35	54	37	169

Table 5.5 - Classification of the days following overreaction – Ripple

Overreaction type	# of pos. ov. days	# of neg. ov. days	# of pos. norm. days	# of neg. norm. days	Tot.
Positive	25	38	25	53	141
Negative	37	35	59	39	170

Table 5.6 - Classification of the days following overreaction – Litecoin

As can be seen from the data shown in tables from 5.3 to 5.6, there is not a precise trend in the days following the overreaction, both positive and negative. An overreaction can be followed both by normal days and by a second overreaction, and it is not possible to understand if the price movement trend is maintained or reversed. More specifically, a positive / negative overreaction can be followed by a day with positive / negative returns or vice versa with more or less the same probability. To understand therefore if there is a momentum effect, with the possibility of making profit, it is necessary to understand what are the average returns of the days are following an overreaction and if their total returns, on the time horizon taken into consideration, are big enough to motivate a trading strategy over them.

Cryptocurrency	Day after pos. ov. avg return	Day after pos. ov. tot return	Day after neg. ov. avg return	Day after neg. ov. tot return
Bitcoin	-0.31%	-47.38%	0.70%	107.04%
Ethereum	-0.47%	-74.11%	0.56%	82.92%
Ripple	-0.33%	-44.11%	0.33%	55.65%
Litecoin	-0.68%	-95.62%	0.64%	108.59%

Table 5.7 - Day after overreaction average and total returns

As can be seen from the data listed in table 5.7, the day following an abnormal daily return is characterised by a contrarian effect and not by a momentum effect. The daily average returns data show that after a positive / negative overreaction there is a negative / positive trend in the price movement, for each of the cryptocurrency examined. What could be done is therefore to exploit this systematic contrarian effect of the days following the overreaction for speculative purposes. The total returns reported in the table in fact reach more than 100% of revenues over the entire time horizon taken into consideration. The average yield, however, always remains below 1%, and it is therefore too low to be able to create a profit taking into account also the transaction costs of the exchanges. This issue will be analysed in detail later in this chapter section dedicated to trading strategy.

Following the analyses previously carried out, it is therefore possible to confirm hypotheses H1 and H2. In particular, the same results of the of Corporal and Plastun (2019) research are obtained:

- An abnormal behaviour is observed on overreaction days. Specifically, the hourly returns detected in the overreaction days are particularly bigger than those during an average day, both positive and negative.
- It is confirmed that the prices trends follow the direction of overreactions until the day ends, driven by a momentum effect.

The hypothesis H3, which is accepted by Corporal and Plastun (2019), is instead rejected. The two researchers find a momentum effect in the days following the overreaction and the presence of a contrarian effect only after BTCUSD positive overreaction and ETHUSD negative overreaction. Differently, in the analyses carried out in this chapter, a contrarian effect is found on all cryptocurrencies after both overreactions, positive and negative, completely excluding the presence of a momentum effect. This difference could be due to the different time horizon used for the analysis and to a different way of calculating the overreaction thresholds. The chapter continues with the development of a trading strategy capable of exploiting the findings obtained so far.

5.3 Trading simulation

In this section we will use the results obtained previously in order to build profitable trading strategies. In particular, two strategies will be tested:

- **Strategy 1:** when it is detected that the current day is an overreaction day, a position is opened in the direction of the overreaction. The position will be considered closed when the overreaction day end
- **Strategy 2:** the trade is opened at the beginning of the day following the overreaction day. A position, opposite to the overreaction, is opened and it will be closed considering different timing indicators.

5.3.1 Strategy 1

The first step in implementing strategy 1 is to decide how to detect an overreaction and sequentially open the positions. The chosen method is to review the hourly returns of each day reported in the hourly granularity dataset, and as soon as the daily return accumulated at a specific hour exceeds one of the two thresholds, positive or negative, open the corresponding position, long or short.
The positive / negative threshold is the one calculated previously, based on the average and standard deviation of the positive / negative days and a coefficient k. Given that a trading strategy is being tested, it is not possible to use the entire back test dataset as the period for calculating the average and standard deviation. Differently, only historical data preceding the trading day under consideration is taken into account. Therefore, a moving average and standard deviation are used, calculated on the previous year. These two values are therefore initialized on the period 01/01/2017 - 31/12/2017, in order to carry out the back test on the period 01/01/2018 - 27/05/2020. The two averages and standard deviations are updated at the end of

each trading day, maintaining a fixed 365 days window. The decision to use a floating window instead of all the data preceding to the trading day under analysis allows to adapt the strategy to the macro-trend of the market more effectively. A single whole average can be inefficient given the trends of the cryptocurrency market in the years examined, in particular 2017 and 2018.

The main problem in opening positions is related to having only hourly granularity data. The cryptocurrency market is generally characterized by high volatility; so, overreactions occur in short periods of time, generally of the order of magnitude of minutes. In addition, most of the momentum effect occurs immediately after the overreaction. This behaviour would therefore require an extremely frequent monitoring of prices, in order to be able to immediately detect if the price has reached the threshold value and open the corresponding position. Not being able to do this with the hourly data, there was the problem of deciding the opening price of the positions. The simplest method would have been to use the closing price of each hourly observation, simulating a trading system that checks the price every hour. This, however, as previously said, would have produced extremely distant results from those of interest, losing the possibility to create good profits. Furthermore, checks at one-hour intervals do not guarantee the opening of a position in the event that the price touches the threshold value in the interval between an observation and the next one. The best solution is to use the hourly closing price only to check if the is higher / lower than the positive / negative threshold, and to use the positive / negative threshold itself as the opening price, as required by the original strategy. In this way, a single hourly closing price, throughout the day, higher / lower than the positive / negative threshold, ensures that the signal value for opening the position has been reached at least once during the day. In addition, the return of the open position thus depends only on two specific values, the threshold and the closing price, becoming fixed and independent of the position opening time. This decision allows to remain consistent with the initial strategy by ensuring that results are useful for its evaluation.

Defined the principle used to implement the strategy 1 it is possible now to perform the simulations on all the cryptocurrencies. The results, obtained with different values of the parameter k, are shown below. Ripple is not tested since its prices are not available from 01/012017, as it was launched later.

k	# of trades	Tot. returns	Avg. returns per positions	# of successful trades	% of successful trades
0	221	300.46%	1.36%	153	69.23%
0.5	123	198.57%	1.61%	82	66.67%
1	72	106.09%	1.47%	48	66.67%
1.5	46	79.64%	1.73%	35	76.09%
2	33	33.59%	1.02%	23	69.70%

Table 5.8 - Bitcoin long positions simulations

k	# of trades	Tot. returns	Avg. returns per positions	# of successful trades	% of successful trades
0	236	202.09%	0.86%	150	63.56%
0.5	138	107.99%	0.78%	93	67.39%
1	82	45.57%	0.56%	46	56.10%
1.5	51	14.41%	0,28%	29	56.86%
2	33	-20.83%	-0.63%	16	48.48%

Table 5.9 - Bitcoin short positions simulations

k	# of trades	Tot. returns	Avg. returns per positions	# of successful trades	% of successful trades
0	219	315.88%	1.44%	150	68.49%
0.5	120	226.78%	1.89%	85	70.83%
1	67	113.22%	1.69%	48	71.64%
1.5	38	82.38%	2.17	30	78.95%
2	25	38.67%	1.55%	19	76.00%

Table 5.10 - Ethereum long positions simulations

k	# of trades	Tot. returns	Avg. returns per positions	# of successful trades	% of successful trades
0	262	287.00%	1.09%	148	56.49%
0.5	151	148.39%	0.98%	92	60.93%
1	90	96.30%	1.07%	58	64.44%
1.5	57	44.28%	0.78%	37	64.91%
2	33	40.95%	1.24%	21	63.64%

Table 5.11 - Ethereum short positions simulations

k	# of trades	Tot. returns	Avg. returns per positions	# of successful trades	% of successful trades
0	185	337.14%	1.82%	123	66.49%
0.5	91	196.11%	2.15%	54	59.34%
1	49	119.30%	2.43%	34	69.39%
1.5	32	80.84%	2.53%	25	78.12%
2	19	57.61%	3.03%	13	68.42%

Table 5.12 - Litecoin long positions simulations

k	# of trades	Tot. returns	Avg. returns per positions	# of successful trades	% of successful trades
0	282	236.06%	0.84%	167	59.22%
0.5	157	124.66%	0.79%	92	58.60%
1	96	71.90%	0.75%	59	61.46%
1.5	63	-5.87%	-0.01%	34	53.97%
2	38	-43.45%	-1.14%	20	52.63%

Table 5.13 - Litecoin short positions simulations

As can be seen from the data shown in tables from 5.8 to 5.13, strategy 1 produces significant profits. In particular, the setup that produces the greatest results in terms of total returns is always the one with the parameter k equal to 0. This means that the method, based on the moving average only, used to identify the overreactions, is the one that produces the higher returns, but not always the most correct. By analysing the success rates in fact, it is possible to notice that at a higher k often corresponds a higher success rate. This testifies the fact that a high k value allows to avoid opening positions on days when there is not or there is a weak momentum. The disadvantages with a higher k are the that fewer positions are opened, and that by using greater threshold values the gains of the trades are truncated, compared to what could have been obtained with a lower k. These disadvantages make strategy 1 highly unprofitable.
Moreover, the high returns produced by the simulations with k equal to 0, with their low percentage of successful trade, ranging from 56.49% to 69.23%, testify that profitable positions give extremely greater returns than the losses of the positions that turn out to be wrong. These results suggest a strong presence of momentum effect on each of the cryptocurrencies analysed, but a difficulty in detecting the overreaction days on which to trade.

5.3.2 Strategy 2

The Strategy 2 consist in opening positions the day after an overreaction day. The trades are opposite to the overreaction that precedes them, in order to take advantage of the contrarian effect noted earlier in this chapter, during the analyses carried out. The detection of an overreaction is performed using the same methodology used for strategy 1. Furthermore, since the best results for strategy 1 were obtained with k equal to 0, this value is kept fixed for all the tests on the strategy 2. Instead, the simulations performed use different timing. The opening time is always the beginning of the day following the overreaction day, but the positions are closed at different time intervals, 6,12,18 and 24 hours. In this it is possible to understand how long there is the contrarian effect, in order to broadly exploit it to make profit.

h	# of trades	Tot. returns	Avg. returns per positions	# of successful trades	% of successful trades
6	220	14.83%	0.07%	117	53.18%
12	220	33.18%	0.15%	123	55.91%
18	220	46.91%	0.21%	121	55.00%
24	220	43.66%	0.20%	110	50.00%

Table 5.14 - Bitcoin positive overreaction simulations

h	# of trades	Tot. returns	Avg. returns per positions	# of successful trades	% of successful trades
6	236	-84.94%	-0.36%	114	48.30%
12	236	-29.85%	-0.13%	120	50.85%
18	236	-24.26%	-0.10%	120	50.85%
24	236	41.74%	0.18%	135	57.20%

Table 5.15 - Bitcoin negative overreaction simulations

h	# of trades	Tot. returns	Avg. returns per positions	# of successful trades	% of successful trades
6	218	6.57%	0.03%	117	53.67%
12	218	46.29%	0.21%	128	58.71%
18	218	82.05%	0.38%	125	57.34%
24	218	61.24%	0.28%	124	56.88%

Table 5.16 - Ethereum positive overreaction simulations

h	# of trades	Tot. returns	Avg. returns per positions	# of successful trades	% of successful trades
6	262	-33.12%	-0.13%	136	51.91%
12	262	-28.17%	-0.11%	140	53.43%
18	262	-31.14%	-0.12%	128	48.85%
24	262	82.05%	0.31%	147	56.11%

Table 5.17 - Ethereum negative overreaction simulations

h	# of trades	Tot. returns	Avg. returns per positions	# of successful trades	% of successful trades
6	184	35.55%	0.19%	104	56.52%
12	184	50.23%	0.27%	100	54.35%
18	184	74.82%	0.41%	108	58.70%
24	184	106.04%	0.58%	113	61.41%

Table 5.18 - Litecoin positive overreaction simulations

h	# of trades	Tot. returns	Avg. returns per positions	# of successful trades	% of successful trades
6	282	-58.64%	-0.21%	132	46.81%
12	282	4.89%	0.02%	147	52.12%
18	282	64.72%	0.23%	145	51.42%
24	282	144.89%	0.51%	152	53.90%

Table 5.19 - Litecoin negative overreaction simulations

As can be seen in tables from 5.14 to 5.19, strategy 2 produces considerable returns. These returns mainly depend on the time selected to close the positions. Considering the Litecoin, the best trade closing time is midnight, both for positions after days of positive and negative overreaction. Instead Ethereum presents the biggest returns by closing the trades at 6 pm, for positive overreactions and at midnight for negative ones. Bitcoin is the one that reports the lowest returns. Furthermore, it can be seen from table 4.15 that in the case of negative overreactions, greater returns can be obtained by exploiting the momentum effect, instead of the contrarian, and closing the position at 6 am. For all other cases, the simulations carried out provide confirmation of the fact that the day after an overreaction day, the cryptocurrencies examined are subject to a contrarian effect, generating returns.

5.3.3 Real world implementation

The results produced by the two strategies report positive returns. However, these results do not guarantee that the application of the two strategies in the real world can lead to profits of an acceptable level. What can heavily affect the ability to create earnings are obviously transaction costs. Therefore, it is important now to understand if the positive results obtained previously with trading simulations are able to generate profits, even taking into account these costs. Having used the data taken from an exchange will allow to make very accurate assessments, using the costs charged by the exchange itself. In particular, Kraken has transaction costs of 0.5% on each trade. Considering the best results obtained in the previous simulations, for each cryptocurrency, we will therefore have the following real returns:

Cryptocurrency	**Overreaction**	**# of trades**	**Avg. P/L per position**	**Tot. P/L**
Bitcoin	Positive	221	0.86%	190.06%
	Negative	236	0.36%	84.96%
Ethereum	Positive	219	0.94%	205.86%
	Negative	262	0.59%	154.58%
Litecoin	Positive	185	1.32%	244.20%
	Negative	282	0.34%	95.88%

Table 5.20 - Strategy 1 results with transaction fees

Cryptocurrency	**Overreaction**	**# of trades**	**Avg. P/L per position**	**Tot. P/L**
Bitcoin	Positive	220	-0.29%	-63.80%
	Negative	236	-0.32%	-75.52%
Ethereum	Positive	218	-0.12%	-26.16%
	Negative	262	-0.19%	-49.78%
Litecoin	Positive	184	0.08%	14.72%
	Negative	282	0.01%	2.82%

Table 5.21 - Strategy 2 results with transaction fees

The data shown in tables 5.20 and 5.21 show the profits obtained in a real trading situation with strategies 1 and 2 respectively. As regards strategy 1, it is be able to generate profits by operating on each cryptocurrency examined, exploiting the momentum effect following the overreaction days, both positive and negative. In particular, strategy 1 has the best results by taking advantage of the momentum that follows a positive overreaction. Strategy 2, on the other hand, proves to be ineffective. The addition of transaction costs mostly leads to obtaining losses or scarce gains. Therefore, the contrarian effect previously found in the days after the overreaction days does not allow to collect concrete profits in a real trading situation.

5.3.4 Results and possible steps further

As already mentioned, the simulations performed on strategy 1 confirmed the possibility of generating profits by exploiting the momentum effect during the overreaction days. Despite the excellent performances obtained, however, there is a low percentage of successful transactions for all the cryptocurrencies take into account. This negative result can be explained by the fact that the heuristic strategy used is not always able to recognize the true days of overreaction, often falling into error. Even using different values of the parameter k, which determines the overreaction thresholds, it is not possible to have significant results, thus suggesting that the most efficient drivers for detecting the abnormal return days are other. The objective of the next chapter is to collect the best drivers to identify the overreaction days in the most efficient way, in order to avoid wrong trades and eliminate the relative losses.

Chapter 6

Machine learning-based trading strategy

In this chapter, machine learning techniques will be presented and used in order to improve the performance of the trading strategy tested previously. In particular, the objective is to identify more precisely the overreaction days in which operate. Before illustrating the strategy used, it is necessary to briefly introduce machine learning and its main characteristics.

6.1 Introduction to machine learning

A first definition of machine learning was given by Arthur Samuel, who describes it as:

"*The field of study that gives computers the ability to learn without being explicitly programmed.*"

A second and more comprehensive definition was later given by Tom Mitchell:

"A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E."

To better understand this definition, it is possible to take chess as an example, where

- E is the experience of playing many games of chess
- T is the task of playing chess
- P is the probability that the program will win the next game

The idea behind the concept of machine learning is therefore to provide computers with the ability to learn and replicate some operations without having been explicitly programmed; these operations are generally predictive or decision-making and based on the data available. In general, any machine learning problem can be assigned to one of the following categories:

Supervised learning: examples of inputs datasets and their respective outputs are provided with the aim of extracting a general rule that associates the input with the corresponding output. Supervised learning problems are divided into regression and classification problems:

- In a regression problem, the objective is to predict results within a continuous output, trying to map input variables to some continuous function

- In a classification problem, the objective is to predict results in a discrete output, trying to map input variables into discrete categories

The supervised learning is characterized by 3 main phases: *training, validation and test phase*.

In supervised learning, the machine must estimate an unknown function f(x) that connects the input variables x to an output variable y. Since the machine does not know the function f(x), its purpose is to learn a hypothesis function h(x) capable of approximating f(x) as much as possible. To do this, it analyses a set of data called *training set* provided by the supervisor. This dataset is composed by the input features and the corresponding outputs. The process can be graphically represented as follows:

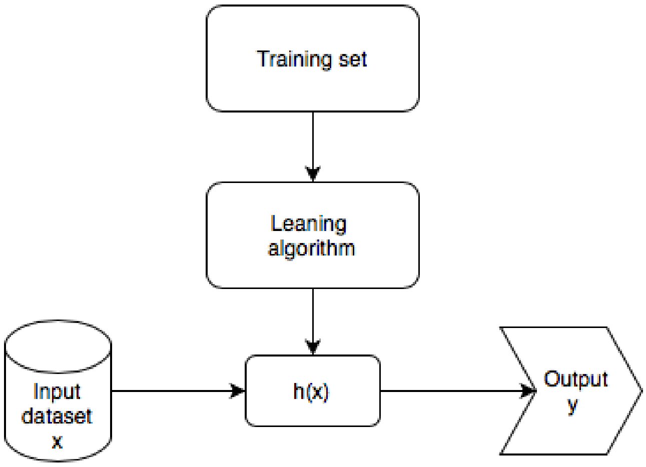


Figure 6.1 – Supervised learning training process

Validation instead is used to fine-tune the model hyperparameters using part of the training dataset. For each learning algorithm a grid of parameters is given, from which the validation extracts the best in order to obtain the highest results in term of accuracy and f1-score.
Accuracy: indicates the ability of the classifier to predict the output correctly. It is calculated as follows: Acc = # correct predictions / tot # of predictions
F1-score**:** measures the accuracy as the mean of precision and recall

- Precision = true positive / (true positive + false positive)
- Recall = true positive / (true positive + false negative)

Last**,** through the test phase is possible to evaluate the results achieved by the learning algorithm, comparing the obtained output with real data. The test is performed by means of a set of inputs and outputs different from the training set, called *test set*. It is essential that these data are never previously viewed by the system.

Unsupervised learning: the inputs provided have neither a defined structure nor associated outputs. The purpose of the calculator is therefore to identify patterns in the inputs in order to reproduce or predict them. It is possible to derive structure from data by clustering the data based on relationships among variables. An example can be given by taking a collection several different genes and find a way to automatically group these genes into groups that are somehow related by different variables, such as lifespan, location, roles, etc. With unsupervised learning there cannot be feedback based on the prediction results.

Reinforcement learning: it is a behavioural learning model where there is an interaction between the calculator and a dynamic environment in order to reach a specific goal. The algorithm receives feedback from the environment and uses them to reach the best outcome. Reinforcement learning is different from other types of supervised learning, because the system learns through trials and errors and it is not trained with the sample data set. An example of use of reinforcement learning is passing a level in a video game.

Deep learning: it is a set of methods belonging to the machine learning family that are capable of providing high level abstraction models for a wide range of phenomena. These techniques have led to the achievement of important advances in various disciplines such as computer vision, natural language processing, facial and vocal recognition, and signals analysis in general. Deep learning incorporates neural networks in successive layers to learn from data in an iterative manner. These complex neural networks are designed to emulate how the human brain works, so computers can be trained to deal with defined abstractions and problems.

In the trading simulations analysed in the previous chapter, considerable returns were found, but also a generally low percentage of successful trades. This because very often prices reached one of the two thresholds, signalling an overreaction and consequently opening a position, but immediately retreated into the normal day price area. Therefore, one of the main problems of the strategy was not to exploit the momentum effect when present, but to efficiently understand which days were of overreaction and which were not. For this reason, this chapter focuses precisely on this problem, trying to improve the results previously obtained. Since the output to be obtained is a discrete set of values - the trading days classification - a classification problem needs to be addressed. In the next paragraphs the development of a classifier able to address this problem, the results obtained, and how these can impact the performance of trading simulations will be shown in detail.

6.2 Classifier design

The ultimate goal of the classifier is to predict whether a trading day is a normal day or an overreaction day, so that this information can be used to generate new trading signals and obtain better investment performance. In this paragraph the main characteristics of the classifier are presented, introducing the input dataset and the features used, the learning algorithm tested and the output variables calculated.

6.2.1 Data utilised

The source is www.kraken.com, one of the main crypto exchange actually operating on the market. The dataset, related to three different cryptocurrency (BTC, ETH and LTC), are downloaded in CSV format from www.cryptodatadownload.com, a website that collect cryptocurrency data from the main crypto exchanges. Each dataset is composed by price and volume data with daily granularity. The structure of the dataset is shown below.

Timestamp	*Open*	*High*	*Low*	*Close*	*Volume Crypto*	*Volume USD*

The data available are from 02/09/2015 to 30/06/2020.

6.2.1.1 Feature engineering

In order to make the classifier more efficient, not only data relating to daily price and volume are used. The raw data relating to prices and volumes (candlestick data), is processed with technical analysis in order to obtain the classifier input dataset, composed by several technical indicators.

As stated by Murphy in his book, "Technical analysis of the financial markets" (1999), technical analysis studies market action, in order to forecast price variations or trends. This is mainly done through reading and analysing charts with historical data and specific technical indicators built upon past values, able to forecast market movements. Technical indicators are defined using mathematical formulae that have price components as variables. Most common indicators use the following values, referred to a single day t:

- Opening price: Ot;
- Closing price: Ct;
- Highest price: Ht;
- Lowest price: Lt;
- Volume exchanged: Vt.

In the following section the indicators utilised are presented. Unless it is specified a different choice, indicators are referred to the closing price.

Trend indicators

Trend indicators should be used to assess trend strength, duration and direction. Also, used with crossover techniques, can signal trend reversal. Here are listed the most common one.

Simple Moving Average (SMA). Simple Moving Average is one of the most used and easy to interpret technical indicator. Each day, its value is given by the arithmetic mean of preceding n components. SMA is not related to a specific price component, nevertheless closing price is the most commonly used. Some traders use mid-point value, calculated as the day's range divided by two or the arithmetic mean between close, highest and lowest prices.

$$SMA_t(n) = \frac{1}{n}\sum_{i=1}^{n} C_{t-i}$$

Moving averages are known as lagged or follower indicators, since the react to changes with a certain delay. They are used to support the idea that a new trend is started or an old one has changed direction, but they cannot predict these events. Also, evaluating the arithmetic mean, the series of values given by moving averages reflects the original one but with smoothed shapes. The parameter n describes the sensitivity to price movements: fast moving averages have a small n; slower ones have a greater n. Technicians use to look for crossovers between SMAs of different speed. When a faster SMA crosses a slower one price trend is likely to reverse.

Exponential Moving Average (EMA). Exponential Moving Average is a weighted average made with past values that do not have all the same weight. EMA places a greater weight and significance on the most recent data points. Its evaluation requires three steps:

1. evaluate the initial value as:

$$EMA_0(n) = SMA_{n+1}(n)$$

2. evaluate the weighting multiplier as:

$$\omega_n = \frac{2}{\mathrm{n}+1}$$

3. evaluate EMA value as:

$$EMA_t(n) = EMA_{t-1}(n) + \omega_n(C_T - EMA_{t-1}(n))$$

Moving Average Convergence Divergence (MACD). This indicator is calculated as the difference between two Exponential Moving Averages, one faster with a short period and one slower with a long period. The classical implementation is:

$$MACD_t(12{,}26) = EMA_t(12) - EMA_t(26)$$

MACD values can be positive or negative. Whenever MACD crosses the zero, a new trend is expected:

- if there is a negative-to-positive transition it suggests an uptrend
- if there is a positive-to-negative transition it suggests a downtrend

Average Directional Index (ADX). ADX is a directional indicator developed by the engineer and technical analyst Welles Wilder. The indicator makes use of Average True Range indicator, Plus Directional Index (+DI) and Minus Directional Index (-DI) directional indicators. While +DI and -DI could indicate trend direction, ADX suggests its strength.

Momentum oscillator

Oscillators are a specific type of indicators that oscillates in a bounded range. Momentum oscillators may be used both to assess trend strength and to highlight overbought or oversold conditions.

- Overbought condition verifies whenever a stock has gained a huge hype on the market and it has been bought way more with respect to normal conditions.
- Oversold condition verifies whenever the stock is massively sold on the market.

Both cases could signal a trend reversal, caused by unsustainable market conditions.
Oscillators are characterized by an upper and a lower band of values. If oscillator enters in either one of the two bands, an atypical market condition could be spot. Typically, values within the upper band suggests an overbought condition, while lower band indicates an oversold condition. In the following paragraphs the most common oscillators are listed, with their relative bands of attention.

Percentage Price Oscillator (PPO). This oscillator monitors the percentage difference between two moving average lines. The most common version uses 12-period and 26-period moving averages, making it the relative counter part of MACD:

$$PPO_t = \frac{EMA_t(12) - EMA_t(26)}{EMA_t(12)} = \frac{MACD_t(12{,}26)}{EMA_t(12)}$$

Relative Strength Index (RSI). RSI has been designed by Wilder. It provides the magnitude of recent price changes, mainly to highlight overbought or oversold condition. The index uses the concept of Relative Strength, with a time frame of 14 past days:

$$RS_t(14) = \frac{\sum_{\mathrm{i} \in \mathrm{U}} C_t - C_{t-1}}{\sum_{\mathrm{i} \in \mathrm{D}} C_t - C_{t-1}}$$

where

- U is the set of up days, whose closing price has been higher than the previous day close
- D is the set of down days, whose closing price has been lower than the previous day close
- The numerator represents the average gain in past 14 days
- The denominator represents the average loss in past 14 days

Then, RSI is evaluated as:

$$RSI_t = 100 - \frac{100}{1 + RS_t}$$

RSI oscillates between 0 and 100. Many traders use 30 and 70 as thresholds respectively for oversold and overbought band borders, more conservative operators may also use 20 and 80 as thresholds. When RSI enters in upper band, the bullish market is likely going to end. In the same way when RSI enters in lower band, the bearish market is ending.

Money Flow Index (MFI). It is an extension of RSI, where also the trading volume has been included. Is defined as:

$$RSI_t = 100 - \frac{100}{1 + MFR_t}$$

where MFR is the Money Flow Ratio substitutes Relative Strength. MFI oscillates between 0 and 100, hence the pairs 30–70 or 20–80 can be used as thresholds for oversold and overbought conditions.

True Strength Index (TSI). This oscillator was introduced by Blau. Its calculation involves several smoothing steps to make the indicator less sensible to noisy variations of stock price. It makes use of Double Smoothed Price Change (DSPC) and Absolute Double Smoothed Price Change (ADSPC) and is computed as follow:

$$TSI_t = 100\,\frac{DSPC_t}{ADSPC_t}$$

TSI can be either positive or negative:

- Positive if prices are going to rise

- Negative if prices are going to fall

As a consequence, the central line crossover is the most common signal situation. Additionally, two symmetrical thresholds could be used to identify oversold and overbought conditions, with values of 25–25 or -50–50.

Stochastic Oscillator (SO). Market theory says that in stocks trending upward prices will close near to the highest recent price and in down trending conditions the same applies for the lowest recent price. Stochastic oscillator has been designed to catch this behaviour.

$$\%K_t = 100\frac{C_t - L_t(14)}{H_t(14) - L_t(14)}$$

Where:

- $H_t(14) = \max(H_i)$
- $L_t(14) = \min(L_i)$
- $i \in \{t-1, t-2, \cdots, t-14\}$

Since the indicator oscillates in [0,100], two positive thresholds define oversold and overbought regions. Common values are 30–70 or 20–80.

Differently Williams %R relates the current closing price with the highest price in the recent window:

$$\%R_t = -100\frac{H_t(14) - C_t}{H_t(14) - L_t(14)}$$

%R is a similar momentum indicator: %R generates the same curve of %K but scaled to different values.

Volatility indicators

These indicators help to detect periods in which market is more volatile, when stocks use to change prices with sharp movements. In such conditions trading become more difficult and different signals should be taken into account. Volatility indicators do not show trends, their strength or directions, but give indications on how smoothly the market is likely going to move around current prices.

Average True Range (ATR). Among the class of volatility indicators, Average True Range (ATR) by Wilder is the most popular one. The volatility is encoded in the absolute measure of True Range (TR).

$$ATR_t(14) = \frac{1}{14}(ATR_{t-1}(14)\ 13) + TR_t$$

Where $TR_t = \max((H_t - L_t), |H_t - C_{t-1}|, |L_t - C_{t-1}|)$

It is clear that True Range is an absolute value that is strictly related to the range of assets considered. Hence ATR values coming from different assets are not comparable. Strong and sharp movements in the price lead to a high True Range and, to a high Average True Range value. The index is monitored by traders because these conditions are commonly accompanied by trend reversal. However, ATR itself should not be used alone but, like other oscillators, should be a support for other trading strategies.

Volume indicators

Volume indicators combine prices values and volumes to give traders indications on sell or buy pressure. One of the rules used by technical traders is that rising in prices should be linked to rises in volumes. A divergence could suggest that trend is not going to last. Here are listed the most common indicators used.

Percentage Volume Oscillator (PVO). It is a momentum oscillator that, like Price Percentage Oscillator, monitors the momentum, or speed of change, smoothing a stock component, in this case the Volume. It is defined as:

$$PVO_t = 100 \frac{EMA_{V,t}(12) - EMA_{V,t}(26)}{EMA_{V,t}(12)}$$

Accumulation Distribution Line (ADL). This volume-based indicator measures the flow of investments on a stock, given is historical prices and volumes values:

$$ADL_t = ADL_{t-1} * MFV_t$$

Where the Money Flow Volume (MFV) is:

$$MFV_t = V_t \frac{[(C_t - L_t) - (H_t - C_t)]}{H_t - L_t}$$

On Balance Volume (OBV). This volume indicator is a cumulative measure introduced by Granville. It measures buying and selling pressures. The volume of each day is added to the total if price closed above opening, while it is subtracted if it was a down day. Its formula is then:

$$OBV_t = OBV_{t-1} \pm V_t$$

Below is the list of all the technical indicators used as input features by the classifier.

Attribute	Description	Intervals
RSMA(5, 20)	Relative difference between SMA(5) and SMA(20)	a <0 <b
RSMA(8, 15)	Relative difference between SMA(8) and SMA(15)	a <0 <b
RSMA(20, 50)	Relative difference between SMA(20) and SMA(50)	a <0 <b
REMA(5, 20)	Relative difference between EMA(5) and EMA(20)	a <0 <b
REMA(8, 15)	Relative difference between EMA(8) and EMA(15)	a <0 <b
REMA(20, 50)	Relative difference between EMA(20) and EMA(50)	a <0 <b
MACD	Moving Average Convergence/Divergence	a <0 <b
AO(14)	Aroon Oscillator	a <0 <b
ADX(14)	Average Directional Index	a <20 <b
WD(14)	Difference between Positive Directional Index (DI+) and Negative Directional Index (DI-)	a <0 <b
PPO(12, 26)	Percentage Price Oscillator	a <0 <b
RSI(14)	Relative Strength Index	a <30 <b <70 <c
MFI(14)	Money Flow Index	a <30 <b <70 <c
TSI	True Strength Index	a <-25 <b <25 <c
SO(14)	Stochastic Oscillator	a <20 <b <80 <c
CMO(14)	Chande Momentum Oscillator	a <-50 <b <50 <c
ATRP(14)	Average True Range Percent: ratio, in percentage, between Average True Range and Close	a <30 <b
PVO	Percentage Volume Oscillator	a <0 <b
OBVP	On Balance Volume Percentage: On Balance Volume index evaluated with percentage variations	a <0 <b

Figure 6.2 – Technical indicators used as classifier input features

6.2.2 Classification model

As previously mentioned, the result to be obtain is a classification of the trading days. In other words, a specific label must be assigned to each analysed day, corresponding to one of the categories. Two different setups, one with three labels and one with two labels, are tested:

3-label setup:

- 1: positive overreaction day
- 0: normal day
- -1: negative overreaction day

2-label setup:

- 0: normal day
- Not 0: overreaction day

In order to train the classifier and to verify its correctness in the test phase, the correct output is needed. For this reason, the labels for each day of the dataset are calculated using the same method utilised in chapter 5, i.e. by the means of the overreaction thresholds. For this reason, the first year of the dataset, which runs from 02/09/2015 to 31/08/2016, cannot be used in the classification process, but only to initialize the thresholds values calculated with moving average of the past 365 days. Therefore, the portion of data available to the classification is:

- Training/validation set: From 01/09/2016 to 30/06/2019 (2 years and 10 months)
- Test set: From 01/07/2019 to 30/06/2020 (1 year)

Therefore, the training/validation set consists of approximately 75% of the classifier available data.

For both setups, five main **learning algorithms** are tested:

- Random forest (RFC)
- K-nearest neighbours (KNN)
- Support vector machine (SVC)
- Logistic regression (LG)
- Gaussian Naïve Bayes (GNB)

6.3 Trading system

The results of the classification are integrated into the heuristic strategy presented in chapter 5, with the aim of improving its performance. In particular, the labels calculated by the classifier are used, together with the thresholds of the heuristic strategy to produce more efficient trading signals for position opening. Following a graphic diagram showing the full process for generating new trading signals.

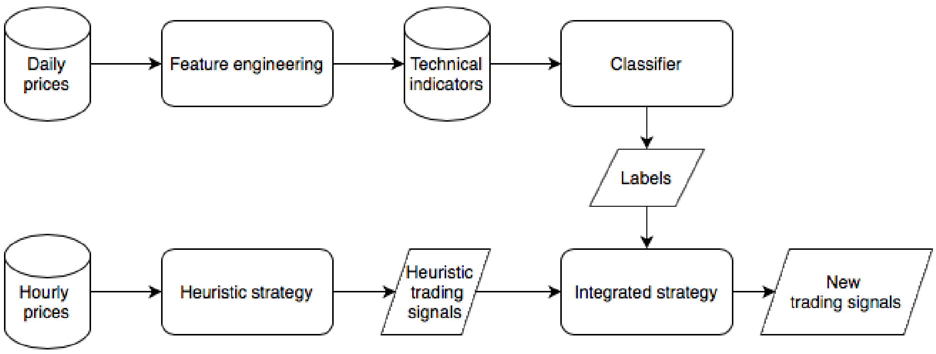


Figure 6.3 – New trading signals generation process

6.3.1 Trading signals generation

In the heuristic strategy, a trading signal is triggered when prices reach one of the two thresholds. In other words, only if a threshold is hit a long or short position is opened. The control on the thresholds is performed every hour, using the same dataset composed by hourly prices presented in chapter 5.

With the integration of the classifier a double check is performed. When one of the two thresholds are touched a second check on the label produced by the classifier for that specific trading day is carried out. If the label confirms that the day is an overreaction day, then the trading signal is triggered, otherwise no position is opened. Since there are two different setups for the classifier, one with three and one with two labels, two different trading strategies have been developed, depending on the number of labels utilised. They are presented in detail below.

3-label strategy

In this strategy the heuristics works in the traditional way, comparing the daily return achieved against the positive and negative thresholds every hour, to decide whether to open a long or short position. Here the difference is that if one of the two thresholds has been exceeded, a second check is first carried out on the label provided by the classifier on that day. Therefore, a long / short position is opened when the positive / negative threshold is exceeded. The position will be opened only if the label of the day is 1 / -1, i.e. if the classifier certifies that it is a day of overreaction, in the direction detected by the heuristic at that moment. Otherwise, no positions will be opened. Below a graph that schematises the operations of this strategy.

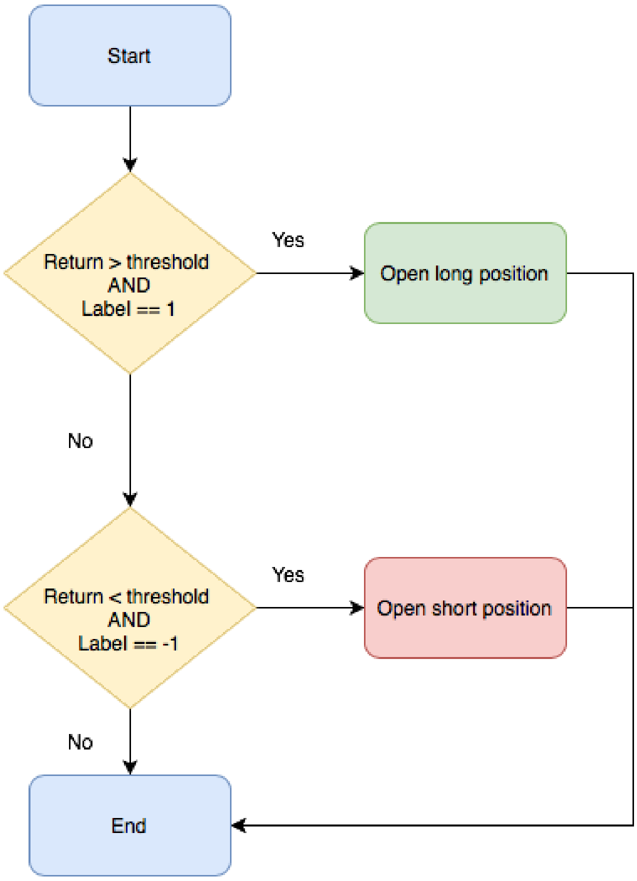


Figure 6.4 – Setup 1 trading strategy flow chart

2-label strategy

This second strategy wants to take advantage of the fact that the accuracy in predicting normal days is far greater than the accuracy in predicting the two different overreaction days. In this case, the second check to decide if open or not a new position is based only on two labels. Therefore, a long / short position is opened when the positive / negative threshold is exceeded and if the label of the day is Not 0, i.e. if the classifier certifies that it is not a normal day. Otherwise, no positions will be opened. Below a graph that schematises the operations of this second strategy.

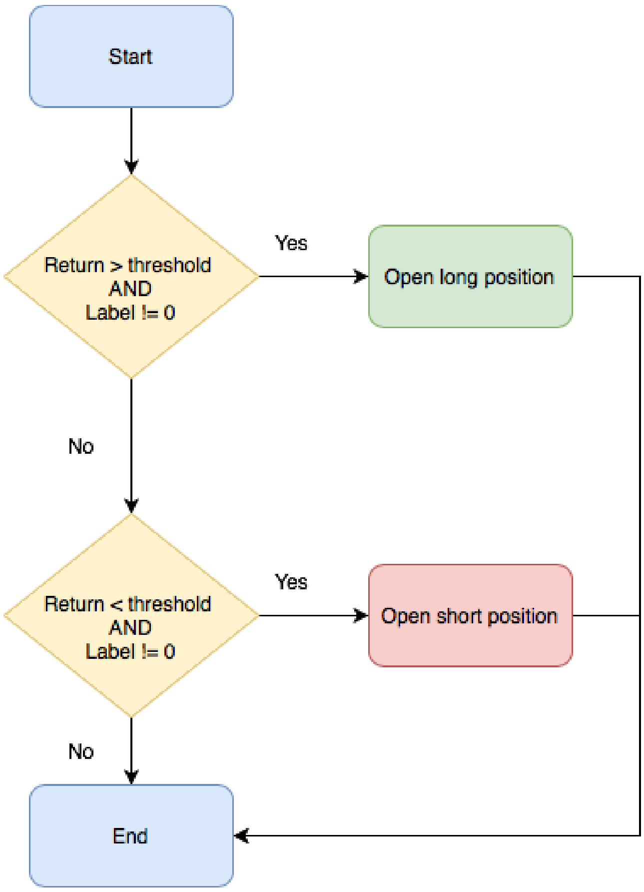


Figure 6.5 – Setup 2 trading strategy flow chart

Chapter 7

Experimental results of the machine learning-based trading strategy

The experiments, whose results will be reported and analysed in this chapter, aim to establish whether the integration of machine learning techniques can improve the performance of the heuristic trading strategy, developed in chapter 5. In particular, the experiment focus is not only on the total profits obtained in the trading period, but also on some risk and resource allocation indicators, of great importance for an efficient trading strategy.

7.1 Experiments design

Three types of experiments are conducted:

1. Classification experiments: in which the ability of the classifier to accurately predict the days of overreaction is tested
2. Trading simulations: where the heuristic strategy is compared with the strategies that integrate the classifier, introduced in chapter 6. In this phase, trading is tested on one cryptocurrency at a time
3. Portfolio simulations: where the heuristic strategy is compared with the strategies that integrate the classifier, trading on all cryptocurrencies. These simulations, more faithful to real trading conditions, will be extremely important to make final considerations on the effectiveness of using ML to exploit the momentum effect on cryptocurrencies trading

The trading period for the trading simulation and the portfolio simulations is from 01/07/2019 to 30/06/2020 (1 year). The profits are calculated by subtracting the transaction fees of 0.5% from each trade, in order better understand the profitability of each strategy in real world situation. Only the first strategy of chapter 5, that invest during the overreaction day, is tested, since the second has shown of not be profitable yet. Below more information about performing experiments are reported.

Machine on which the experiments are carried out:

Machine:	MacBook Pro (13-inch 2017)
Operative system:	macOS High Sierra (version 10.13.6)
Processor:	2.3 GHz Intel Core i5
RAM:	8 GB 2133 MHz LPDDR3
Graphic card:	Intel Iris Plus Graphics 640 1536 MB

Experiments execution time:

Classification experiments	~ 20 seconds
Trading simulations	~ 10 seconds
Portfolio simulations	~ 20 seconds

7.2 Experiments results

In this paragraph all experiment results are reported and commented.

7.2.1 Classification results

Below are the results obtained by the classifier using the five different algorithms taken into consideration, both for the 3-label and 2-label setups.

Learning algorithms	Metrics	BTC	ETH	LTC
RFC	Accuracy	0.52	0.47	0.48
	F1-score	0.51	0.48	0.50
KNN	Accuracy	0.54	0.52	0.51
	F1-score	0.53	0.51	0.53
SVC	Accuracy	0.57	0.54	0.66
	F1-score	0.50	0.51	0.57
LG	Accuracy	0.47	0.59	0.65
	F1-score	0.46	0.52	0.56
GNB	Accuracy	0.52	0.56	0.62
	F1-score	0.49	0.51	0.56

Table 7.1 – 3-label setup classifier results

Learning algorithms	Metrics	BTC	ETH	LTC
RFC	Accuracy	0.57	0.55	0.57
	F1-score	0.56	0.55	0.58
KNN	Accuracy	0.57	0.6	0.61
	F1-score	0.53	0.57	0.60
SVC	Accuracy	0.58	0.54	0.66
	F1-score	0.51	0.54	0.58
LG	Accuracy	0.58	0.55	0.61
	F1-score	0.54	0.54	0.60
GNB	Accuracy	0.56	0.60	0.62
	F1-score	0.52	0.54	0.59

Table 7.2 – 2-label setup classifier results

The accuracy and f1-score metrics reported in tables 7.1 and 7.2 are a weighted average of the metrics calculated on each label. The results obtained by the classifier show a good efficiency by all the tested algorithms in predicting the class of trading day. In particular, the 2-label setup shows the best results, as expected. Appendix C lists the parameters of each algorithm chosen in the validation phase, by means these results were obtained. After the classification phase, in which good results has been obtained, the output of the classifier must be efficiently used in order to improve the trading performance.

7.2.2 Trading simulations results

Following are reported the results obtained by using the heuristic strategy and the two strategy that integrate machine learning.

Strategy	Tot. positions	Successful trades	Tot. return	Avg. return	Profit
Heuristic	193	60.10%	152.32%	0.79%	55.82%
RFC (3L)	30	63.34%	36.15%	1.21%	21.15%
KNN (3L)	32	71.88%	52.23%	1.63%	36.23%
SVC (3L)	8	62.50%	10.57%	1.32%	6.57%
LG (3L)	29	72.41%	28.61%	0.99%	14.11%
GNB (3L)	22	59.09%	4.95%	0.23%	-6.05%
RFC (2L)	48	70.83%	51.88%	1.08%	27.88%
KNN (2L)	32	71.88%	37.19%	1.16%	21.19%
SVC (2L)	15	66.67%	11.03%	0.74%	3.53%
LG (2L)	34	73.53%	39.74%	1.17%	22.74%
GNB (2L)	35	62.86%	23.99%	0.69%	6.49%

Table 7.3 – BTC trading simulation results

Strategy	Tot. positions	Successful trades	Tot. return	Avg. return	Profit
Heuristic	188	64.36%	243.82%	1.30%	149.82%
RFC (3L)	43	76.74%	90.92%	2.11%	69.42%
KNN (3L)	31	80.65%	75.78%	2.44%	60.28%
SVC (3L)	21	66.67%	50.28%	2.39%	39.78%
LG (3L)	8	75.00%	26.43%	3.30%	22.43%
GNB (3L)	17	64.71%	33.23%	1.95%	24.73%
RFC (2L)	58	72.41%	118.17%	2.04%	89.17%
KNN (2L)	32	68.75%	68.93%	2.15%	52.93%
SVC (2L)	57	70.18%	107.18%	1.88%	78.68%
LG (2L)	56	67.86%	50.35%	0.90%	22.35%
GNB (2L)	21	57.14%	23.88%	1.14%	13.38%

Table 7.4 – ETH trading simulation results

Strategy	Tot. positions	Successful trades	Tot. return	Avg. return	Profit
Heuristic	183	59.56%	207.85%	1.14%	116.35%
RFC (3L)	41	51.22%	37.82%	0.92%	17.32%
KNN (3L)	41	58.54%	39.03%	0.95%	18.53%
SVC (3L)	2	100.00%	5.19%	2.60%	4.19%
LG (3L)	3	66.67%	4.16%	1.39%	2.66%
GNB (3L)	11	54.55%	6.27%	0.57%	0.77%
RFC (2L)	59	61.02%	76.74%	1.30%	47.24%
KNN (2L)	45	15.95%	82.58%	1.84%	60.08%
SVC (2L)	12	83.33%	29.76%	2.48%	23.76%
LG (2L)	48	70.83%	79.59%	1.66%	55.59%
GNB (2L)	29	62.07%	35.09%	1.21%	20.59%

Table 7.5 – LTC trading simulation results

Some important considerations can be made by analysing the results obtained.

I. The **total number of open positions** is considerably lower in simulations that employ the strategy that uses the classifier. On average, only 20% of the operations that would have carried out the heuristic strategy pass the double check of the strategy that integrates the classifier.

II. For almost all classification algorithms, the percentage of **successful trades** increases compared to the heuristic strategy. Therefore, the decrease in the number of open positions by means of a second check on the label produced by the classifier proved to be an efficient mechanism to eliminate wrong positions and potential losses.

III. The **total return** of the heuristic is considerably higher than all the solutions that integrate the different classification algorithms, both with 3 and with 2 labels. **Profits** from heuristics also are the best, even if heavily plagued by high transaction costs given by the large number of open positions.

IV. Although the total return is higher in the heuristic strategy, it has a significantly lower **average return** per position. Also, in this case the strategies that make use of the classifier are better as they can leverage on a smaller number of trades and of higher quality.

V. Generally, the **best results** in all the analysed metrics are obtained with the 2-labels strategy, since it is easier for the classifier to forecast the presence of a normal day or not than distinguish the two type of overreactions.

Another important issue must be taken into consideration. The higher profits obtained from the heuristic strategy are the result of a greater number of trades and therefore of a greater resources allocation. This problem was not posed in the previous simulations as it was carried out on one single cryptocurrency each time. On the other hand, it is more interesting to analyse the behaviour of the various strategies with portfolio simulations that include several cryptocurrencies at the same time, closer to the real-world context, and for this reason of more interest to professionals and traders.

7.2.3 Portfolio simulations results

The portfolio simulations performed include all three cryptocurrencies analysed so far: BTC, ETH and LTC. The objective of this analysis is to simulate a more realistic trading system that invest in more than one crypto, facing all the problem this leads, such as resources allocation. The amount of resources used for each trade varies according to the strategy used.

Heuristic strategy

Since using the heuristic strategy, it is not possible to know in advance how many positions will be opened in a single day as long as the price of one of the cryptocurrencies considered do not exceed the thresholds, the investable resources are equally divided between them. This can lead to a big disadvantage as if during a day only the price of a specific cryptocurrency exceeds a threshold, the position opened will have only limited resources available, leaving the others unused.

Classifier strategy

The problem of resource allocation found in the heuristic strategy here can be addressed using the labels produced by the classifier. Since the labels are used to decide whether or not to open a position and that are available at the beginning of each trading day, they can be used to calculate the maximum number of tradable cryptos during each day. In this way the resources available for daily investments will no longer be divided among all the cryptocurrencies considered by the portfolio, but only by the tradable one, able to pass the double check on threshold and label. However, if during the day one of the cryptocurrencies considered tradable does not reach one of the thresholds, the resources assigned to it will remain unused.

Following the portfolio simulations result are reported, for both strategies:

Strategy	Tot. profit	Avg. return	Volatility	Drawdown	Avg. trade #
Heurstic	143.92%	0.43%	4.01%	-26.50%	2.16
RFC (3L)	84.01%	0.84%	2.66%	-3.53%	1.52
RFC (2L)	156.37%	0.87%	3.03%	-5.79%	1.43
KNN (3L)	68.54%	0.94%	2.64%	-3.26%	1.76
KNN (2N)	89.47%	0.83%	3.12%	-4.41%	1.26
SVC (3L)	47.18%	1.45%	3.69%	-2.69%	1.11
SVC (2L)	118.82%	1.24%	6.63%	-28.95%	1.11
LG (3L)	36.34%	0.90%	2.68%	-4.41%	1.11
LG (2L)	64.13%	0.63%	4.41%	-28.95%	1.39
GNB (3L)	13.13%	0.33%	2.88%	-5.79%	1.19
GNB (2L)	39.95%	0.52%	3.08%	-5.79%	1.23
Average-ML	71.69%	0.86%	3.48%	-9.36%	1.31
Average	78.26%	0.82%	3.53%	-10.92%	1.39

Table 7.6 – trading simulations results

As can be seen from the data reported in table 7.6, the use of machine learning techniques, integrated with the heuristic strategy, make the trading more efficient and usable in a more realist contests, where a portfolio of cryptos is considered instead that a single one. The average return per trade is significantly higher for strategies that integrate the classifier. This combined with the better resources' management, allows to maximize the returns of each trading day, avoiding to waste money allocating them to not tradable crypto or unprofitable operations. Another important aspect that arises from the comparison of the heuristic strategy and those based on machine learning is risk. As can be seen from the data shown in table 7.6, the heuristic strategy is subject to a high volatility, and this leads to extremely negative days in which large losses are faced. To better understand this evidence following are reported the equity lines with the drawdowns of the heuristic strategy and the best performing machine learning strategy (RFC 2) in terms of total profits.

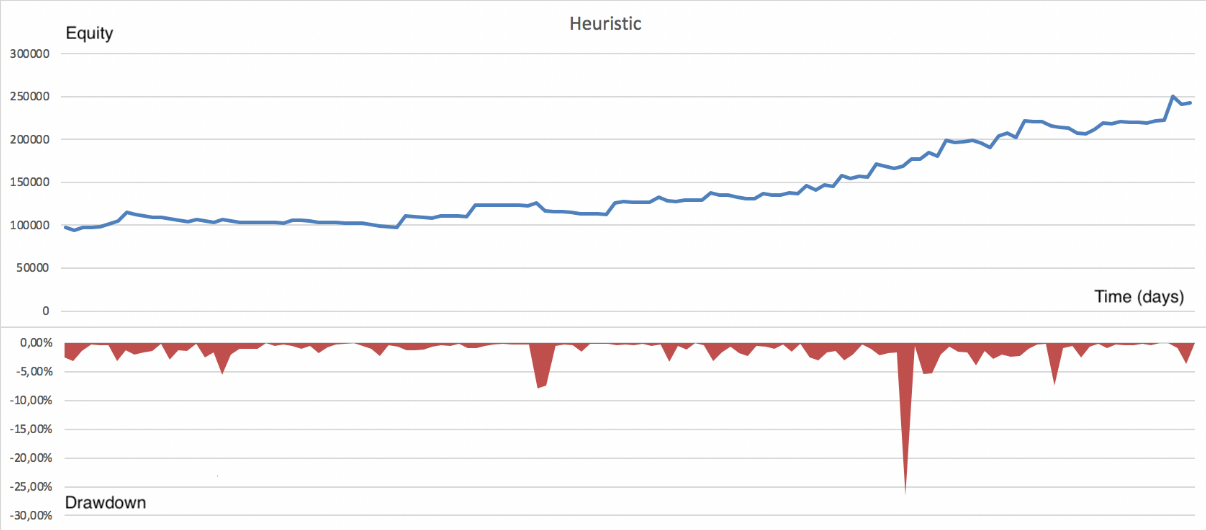


Figure 7.1 – Portfolio equity of heuristic strategy

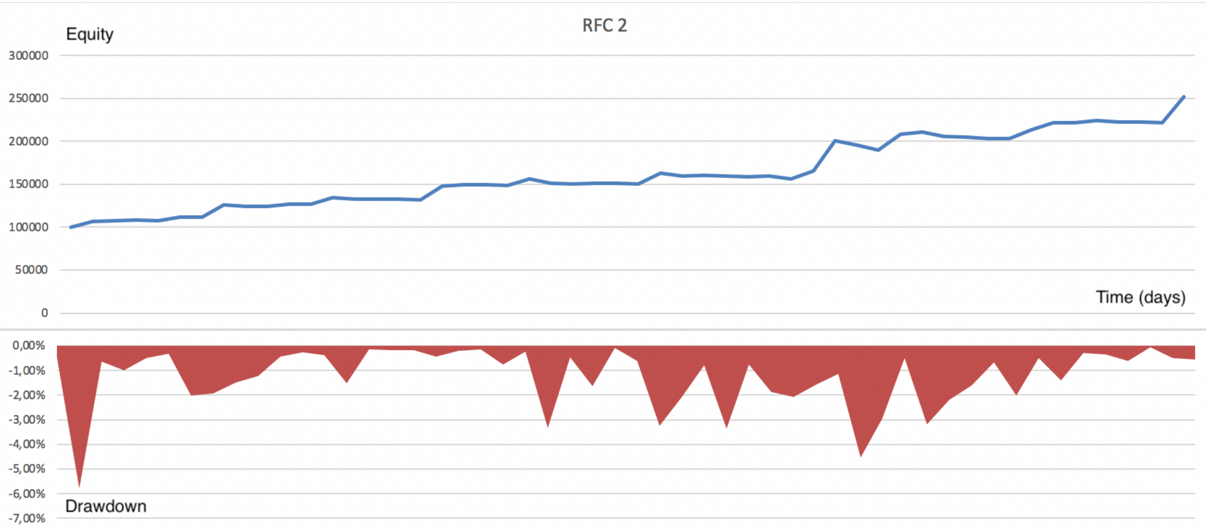


Figure 7.2 – Portfolio equity of the RFC 2 strategy

Figures 7.1 and 7.2 show how RFC2 strategy is able to deliver as good returns as heuristics, but with lower risk. For the RFC2 strategy in fact the magnitude of the drawdown remains below 5%, without seriously affecting the equity of the portfolio. The heuristic, on the other hand, is more vulnerable to volatility, repeatedly losing more than 5% of equity, with a maximum of 26.5% in a single trading day. By extending the portfolio simulations to a period longer than one year, it is likely to face more adverse conditions that could cancel large part of the portfolio's equity. Looking at the result it is possible to assess that the integration of the classifier improves profits and gives the opportunity to reduce risks and increase the scalability of the strategy. This allows traders to invest in a greater number of cryptocurrencies, making the strategy more scalable, or to implement other strategies, in order to diversify the portfolio.

Conclusions

The investigation carried out in this thesis has led to some considerable evidence regarding the behaviour of the cryptocurrency market that can be of interest to both academics and investors. Following the investigation performed on the financial theory it is possible to state that the cryptocurrency market is affected by a momentum effect. In particular, the crypto market has shown signs of some of the phenomena studied by behavioural finance and identified as the cause of the momentum effect.

After verifying the validity of the research question from a theoretical point of view, the investigation has proceeded to verify it from an empirical point of view, first looking for the factor triggering the momentum, and then observing the behaviour of prices after that. According to Caporale and Plastun, the momentum effect is experienced following a sharp change in price on a daily basis and lasts until the following day. These overreaction days are characterized by a price behaviour different from the normal days and are therefore recognizable. The investigation therefore focused on verifying these hypotheses, checking the presence of anomalous days, the possibility of identifying them effectively and the behaviour of prices after having identified them. Following the analyses carried out, the hypotheses of Caporale and Plastum were confirmed.

Having verified the presence of the momentum effect and identified the cause, the objective was to exploit this information to generate a profit through trading. The first strategy used, based on a heuristic algorithm, proved to be profitable but presents some substantial problems that do not allow its implementation in the real world. The high number of transactions carried out by this strategy in fact dramatically increases costs, risk and the amount of resources that are allocated, making it inefficient.

The introduction of a classifier to solve these problems has proved to be a winning choice. This, by accurately identifying the days of overreaction, was able to eliminate numerous wrong trades, increasing profitability. Furthermore, the use of machine learning makes it possible to reduce risks and increase the scalability of the strategy, allowing traders to invest in a greater number of cryptocurrencies or to implement other strategies diversifying the portfolio.

Some further steps can be taken.

The analyses carried out used datasets with daily and hourly granularity. The decision as to whether or not to open a position was made on an hourly basis. However, modern high frequency trading strategies, and the APIs provided by modern exchanges, allow investors to control prices more closely. To make the results of the strategies proposed in this work closer to a real trading system, new tests could be carried out on a smaller granularity dataset, of the order of the minute.

A second interesting path is analysing the momentum effect also on other cryptocurrencies, especially those with lower market capitalization. These are characterized by high volatility and could be extremely profitable. Once the most promising cryptocurrencies have been identified, the portfolio simulations could then be extended to a wider range of coins, so as to make the most of the ability to effectively allocate the resources of the strategy that makes use of machine learning.

Lastly, improve the method of detecting the overreaction days in which to invest. This can be done both by changing the way in which the heuristic thresholds are computed, basing it not only on moving average and standard deviation, and by operating on the machine learning side, testing new algorithms, providing different inputs and better tuning through validation.

Appendix A

Figure A.1 – Bitcoin avg. hourly returns on over. and normal days (positive and negative)

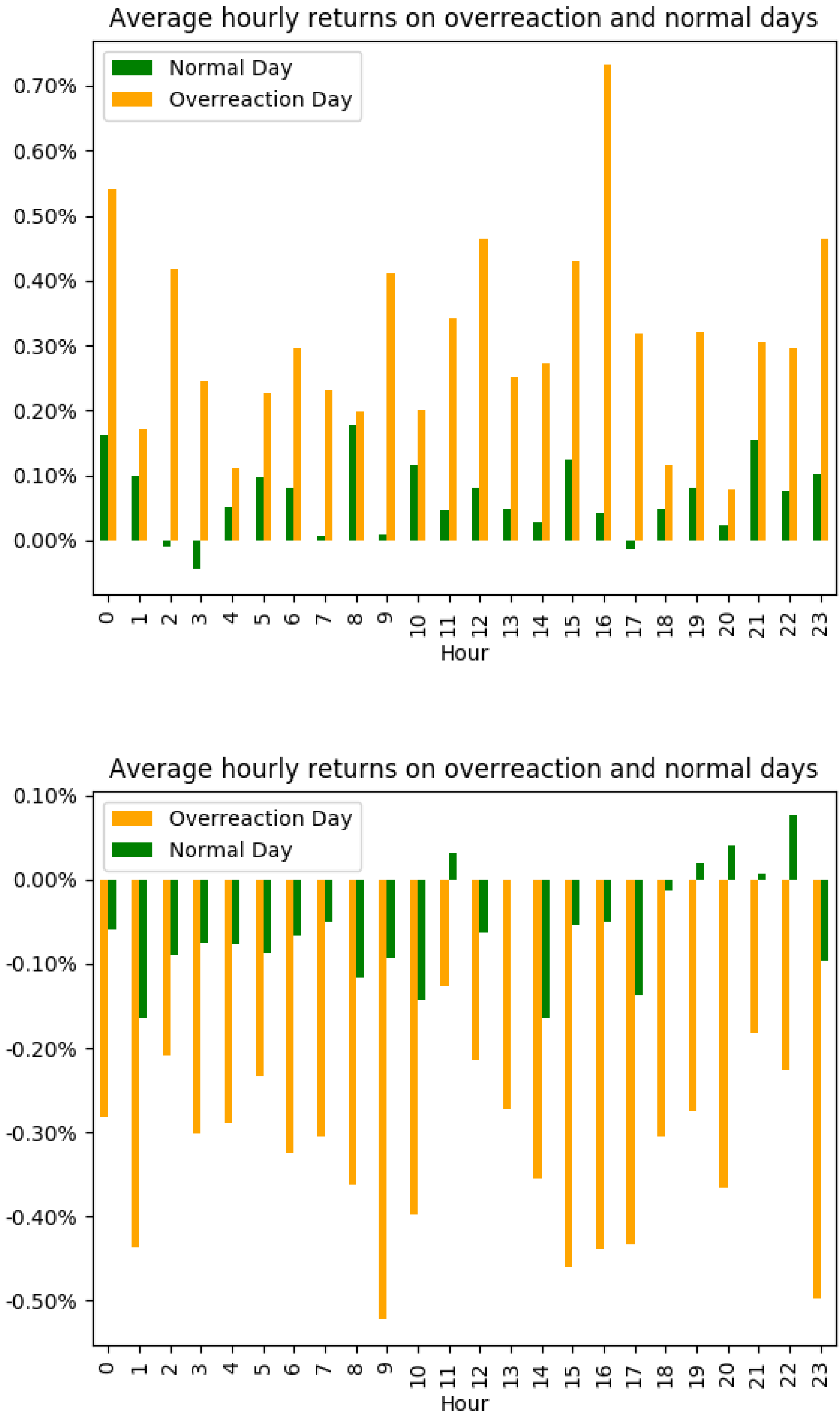
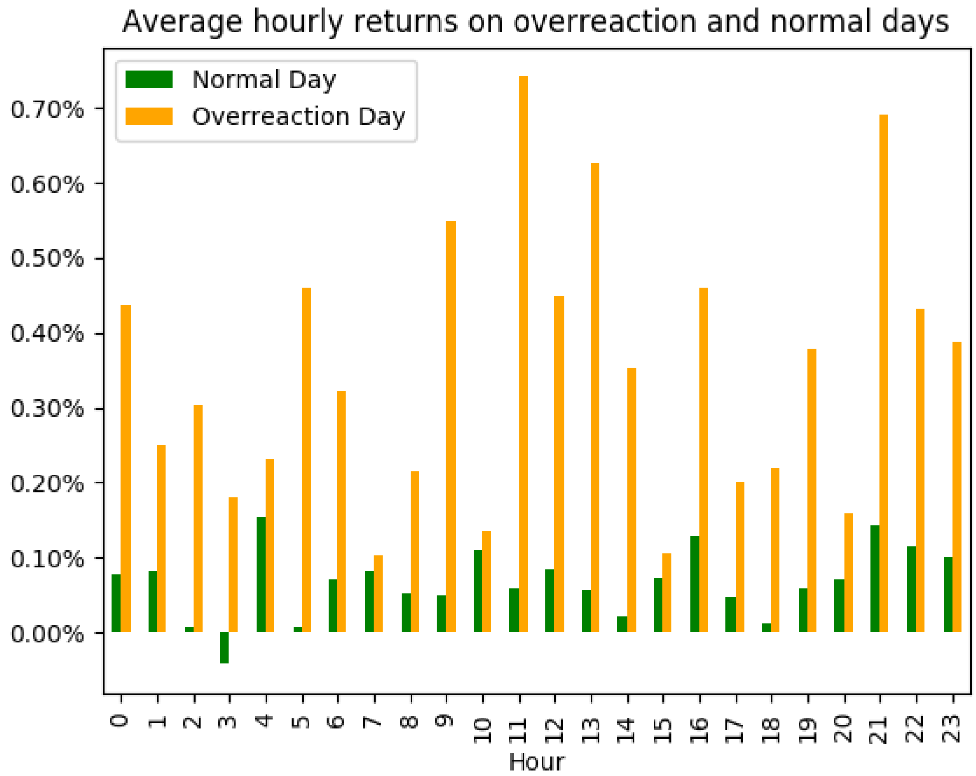


Figure A.2 – Ethereum avg. hourly returns on over. and normal days (positive and negative)



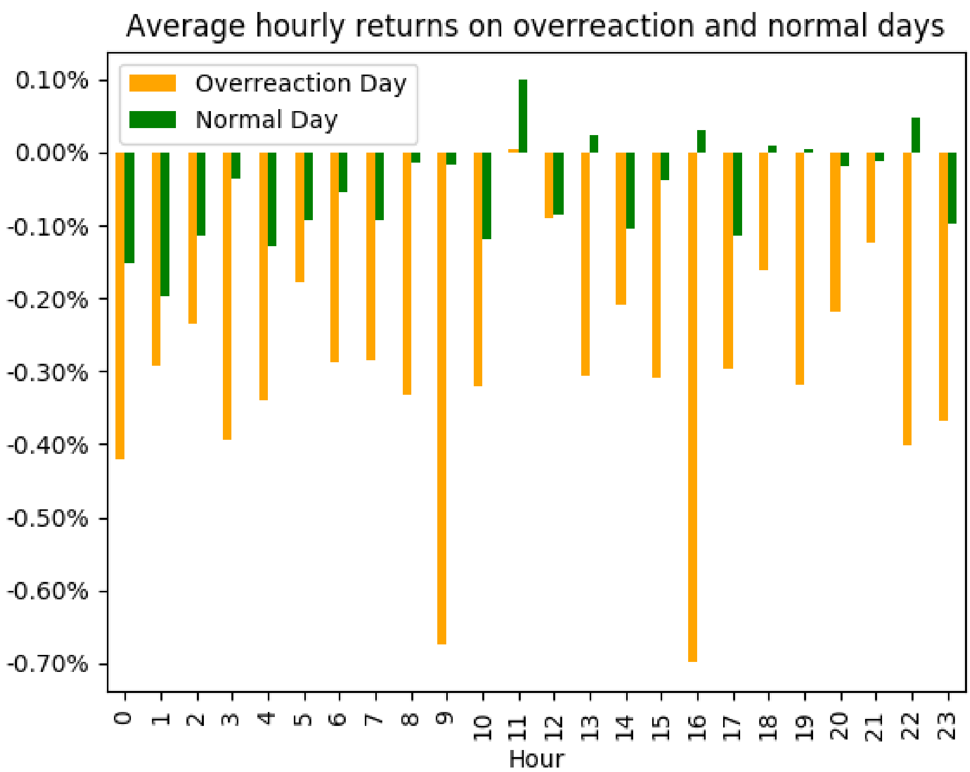


Figure A.3 – Ripple avg. hourly returns on over. and normal days (positive and negative)

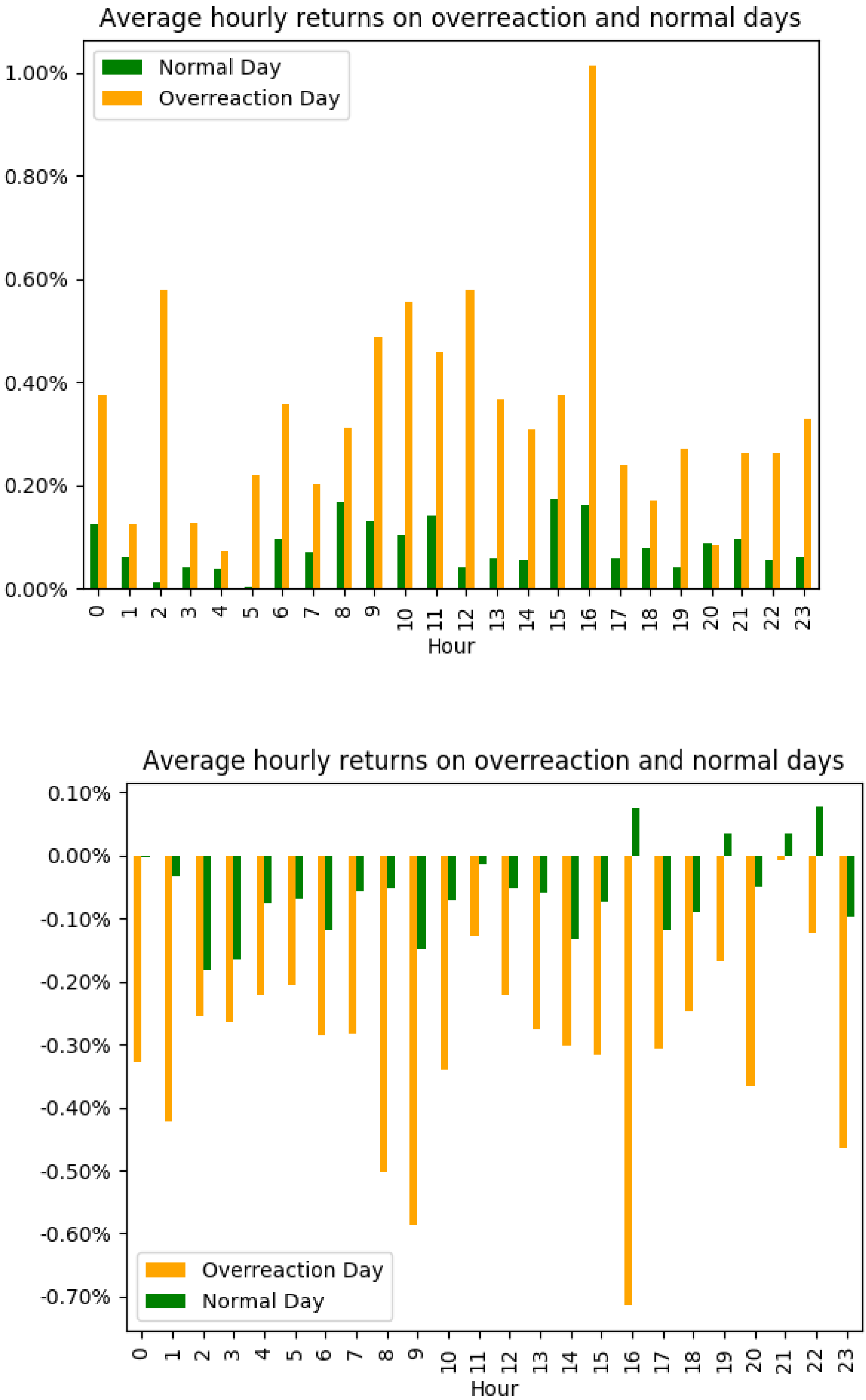
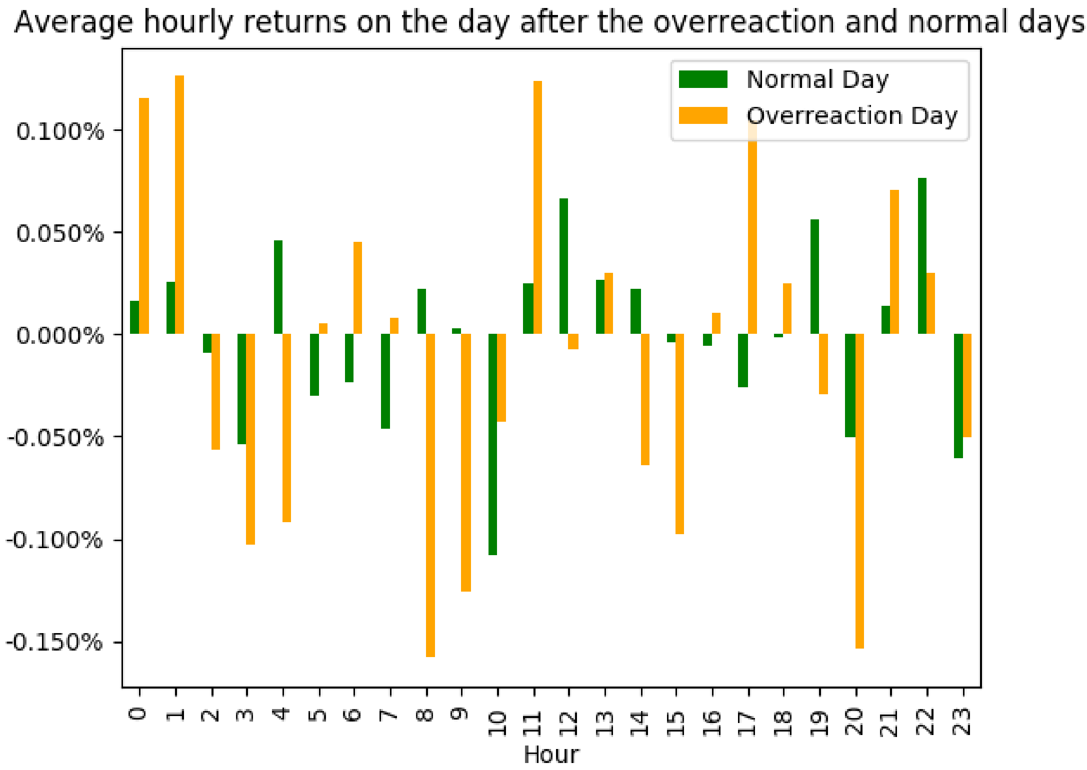


Figure A.4 – Litecoin avg. hourly returns on over. and normal days (positive and negative)

Appendix B



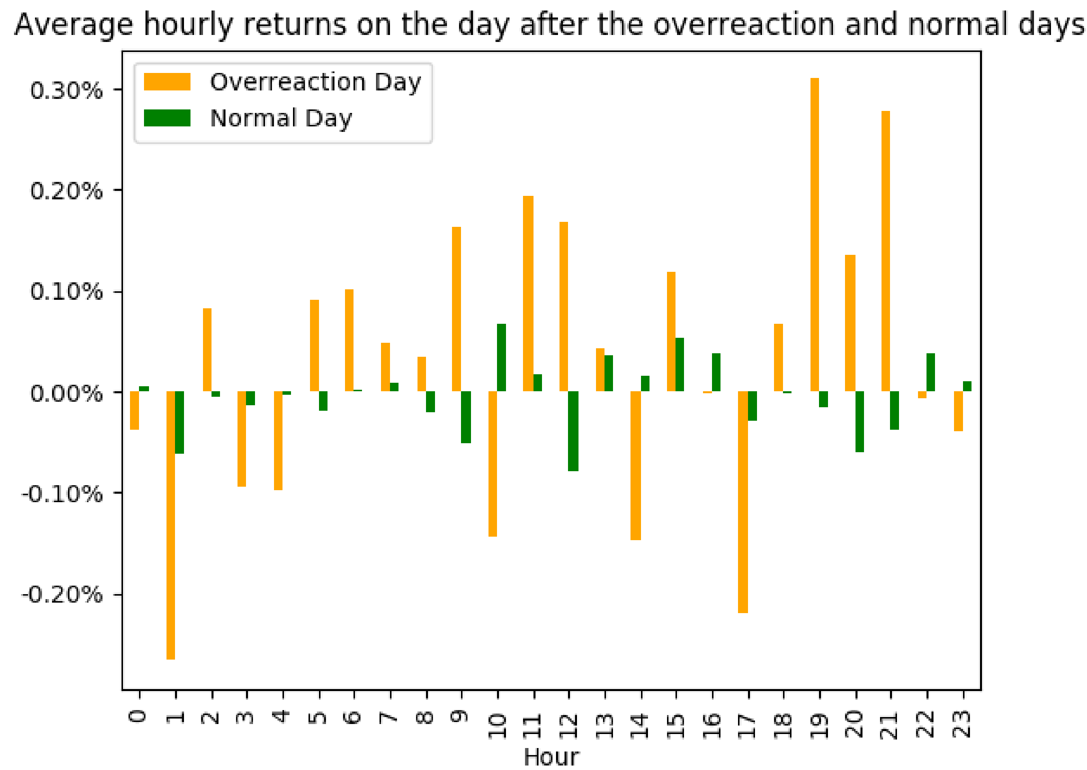
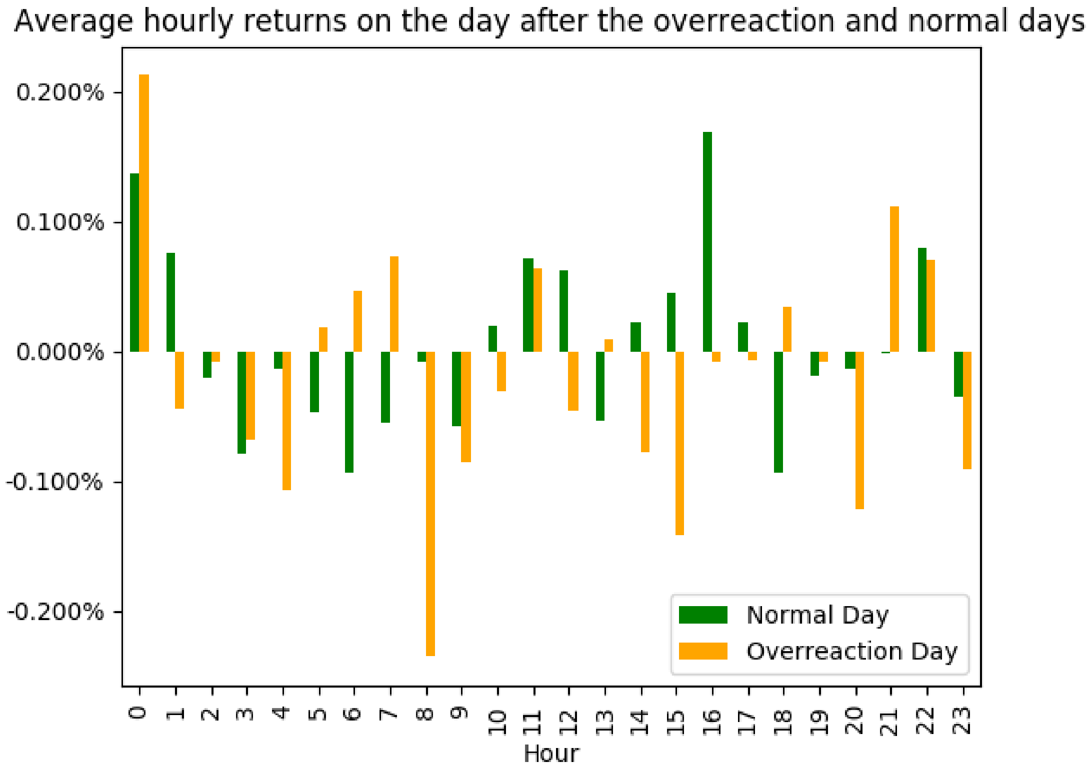


Figure B.1 – Bitcoin avg. hourly returns on the day after over. and normal days (positive and negative)



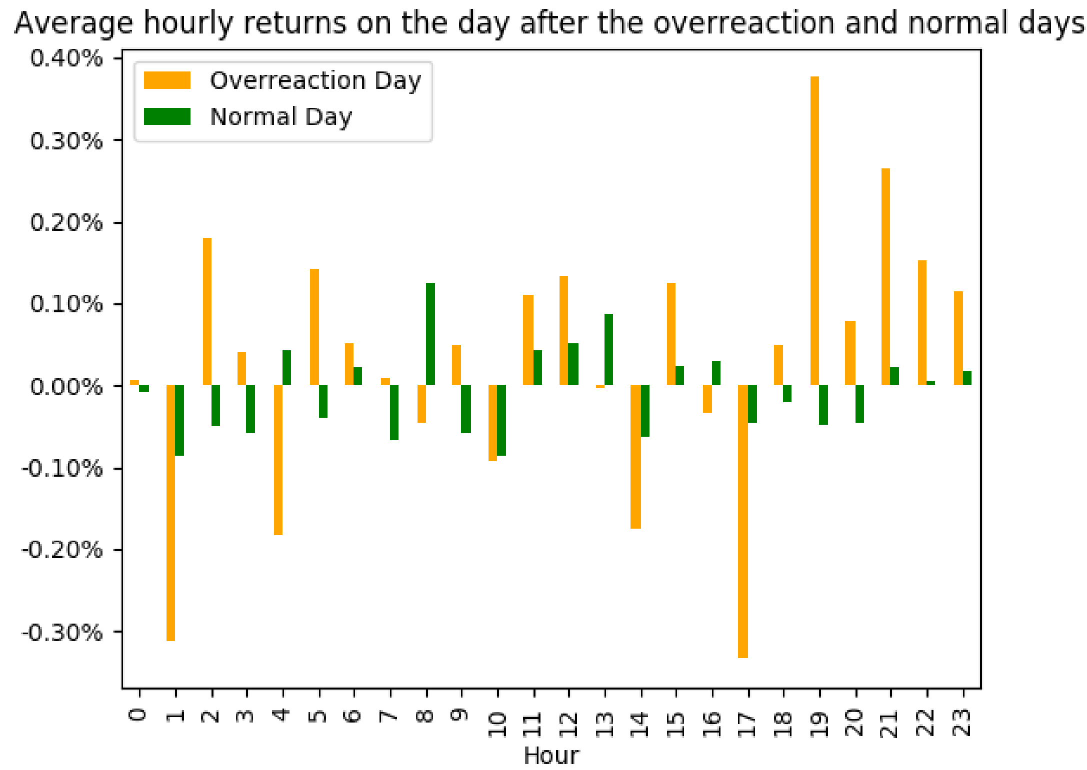
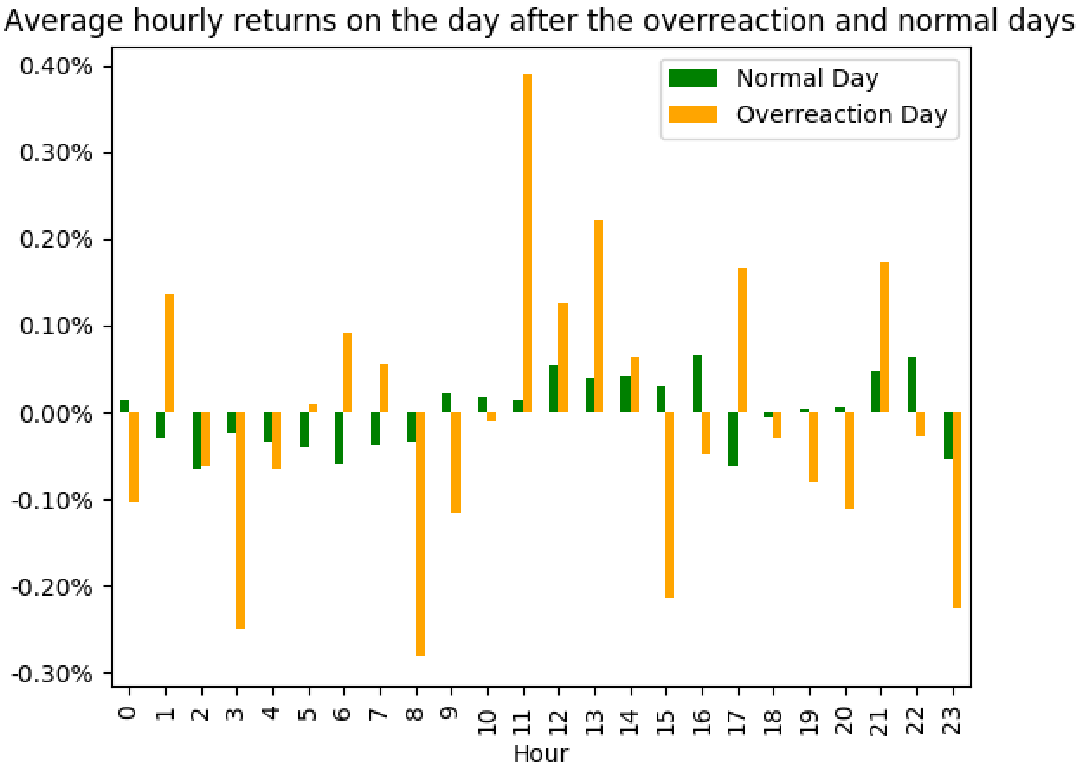


Figure B.2 – Ethereum avg. hourly returns on the day after over. and normal days (positive and negative)



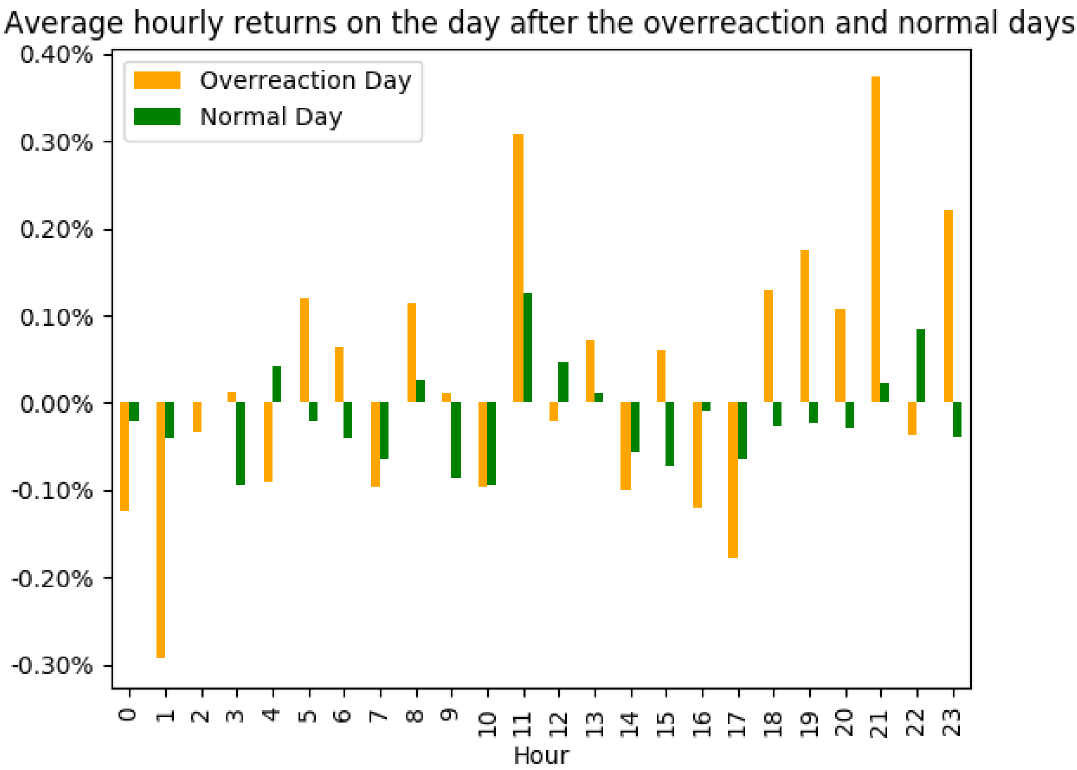
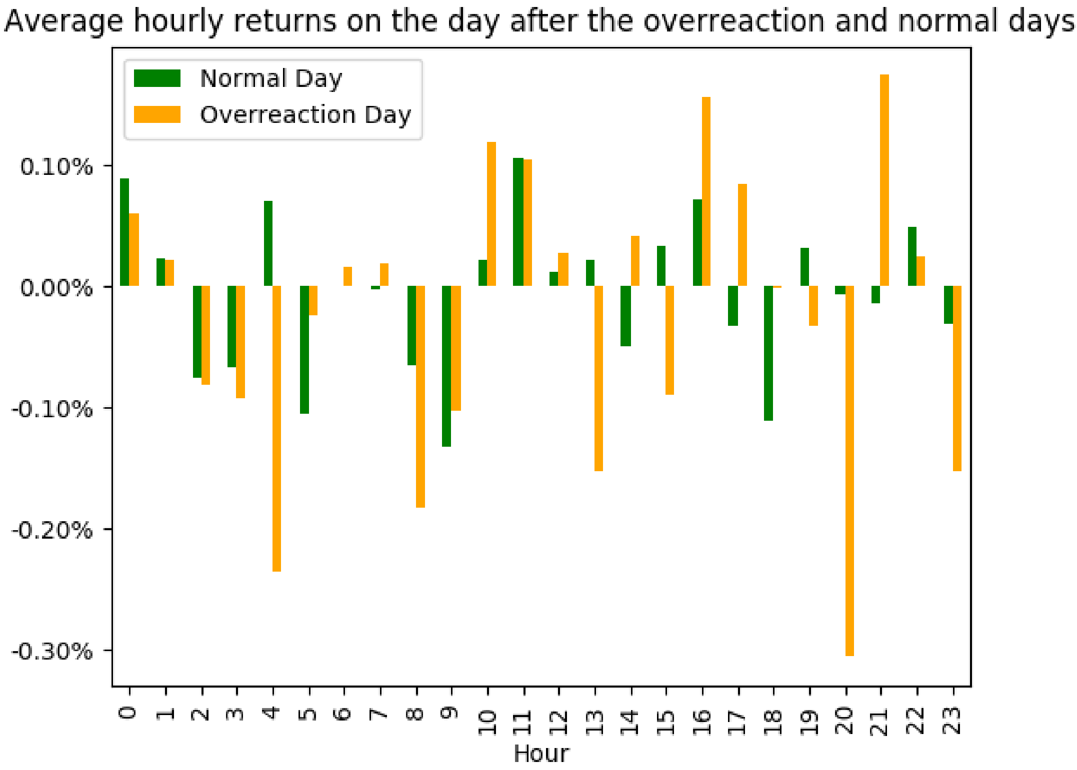


Figure B.3 – Ripple avg. hourly returns on the day after over. and normal days (positive and negative)



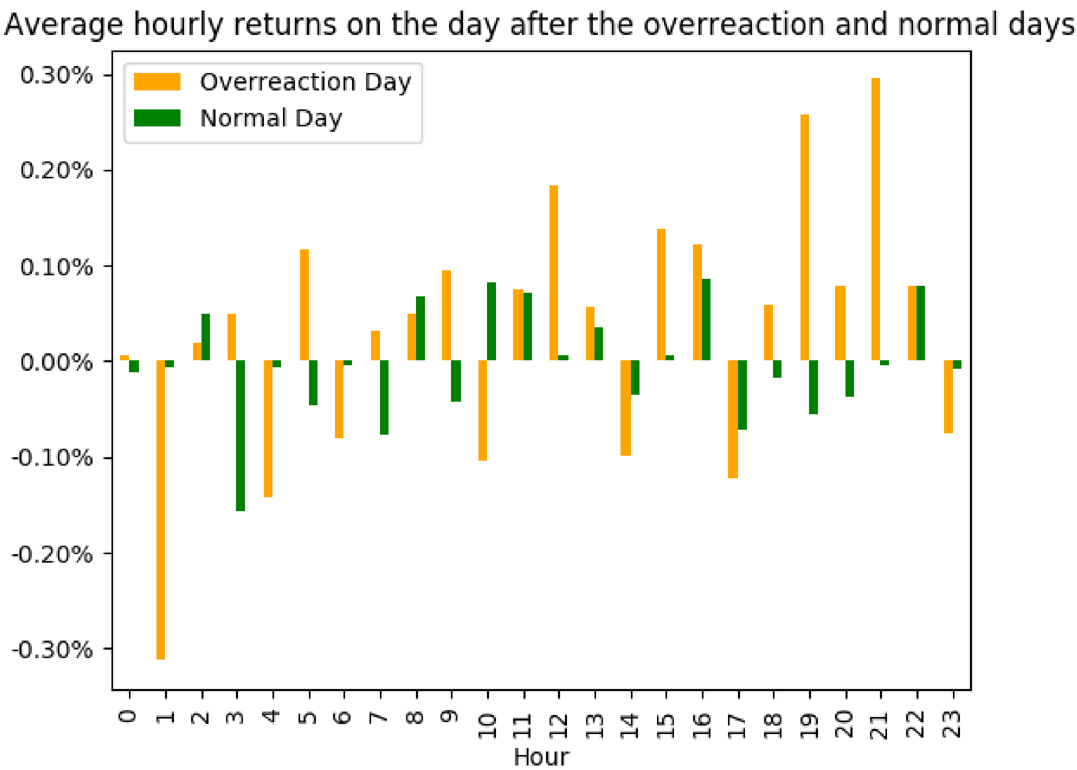


Figure B.4 – Litecoin avg. hourly returns on the day after over. and normal days (positive and negative)

Appendix C

Algorithm	Grid parameters
RFC	▪ 'criterion': ['gini', 'entropy'] ▪ 'min_samples_split': [0.01, 0.05] ▪ 'min_samples_leaf': [0.005, 0.01]
KNN	▪ 'weights': ['uniform', 'distance'], ▪ 'n_neighbors': [3, 5, 7], ▪ 'algorithm': ['ball_tree', 'kd_tree']
SVC	▪ 'kernel': ['linear', 'poly', 'rbf'], ▪ 'degree': [3, 4, 5], ▪ 'C': [0.001, 0.01, 1, 10, 50]
LG	▪ 'solver': ['newton-cg', 'lbfgs', 'liblinear'], ▪ 'penalty': ['l1', 'l2'], ▪ 'C': [0.01, 0.1, 1, 10]
GNB	none

Table C.1 – Grid parameters of validation phase

Algorithm	Parameters	BTC	ETH	LTC
RFC (3L)	Criterion: Min_sample_split: Min_samples_leaf:	Entropy 0.01 0.005	Entropy 0.01 0.01	/ 0.01 0.005
RFC (2L)	Criterion: Min_sample_split: Min_samples_leaf:	Entropy 0.05 0.005	Entropy 0.05 0.01	/ 0.01 0.01
KNN (3L)	Weights N_neighbors algorithm	Distance 7 Ball_tree	Distance / Ball_tree	Distance 7 Ball_tree
KNN (2L)	Weights N_neighbors algorithm	/ 7 Ball_tree	/ 3 Ball_tree	/ 3 Ball_tree
SVC (3L)	Kernel Degree C	Poly 4 0.01	Poly / 1	Poly 4 0.01
SVC (2L)	Kernel Degree C	Poly 4 0.01	Linear / 1	Poly 5 1
LG (3L)	Solver Penalty C	Newton-cg / 10	Liblinear L1 0.1	Liblinear L1 0.1
LG (2L)	Solver Penalty C	Liblinear L1 0.1	/ / 10	Liblinear L1 0.1

Table C.2 – Best setups from validation phase

Bibliography

Caporale G. M. & Plastun A. (2019), "Momentum effect in the cryptocurrency market after one-day abnormal returns", *CEsifo working papers*, 7917 October 2019

Søndergaard M. E. & Risager O. (2010), "The momentum effect on stock markets, a literature reviews and an empirical study", *Copenhagen Business School - Institute of Accounting and Auditing*, Master Thesis July 2010

Fang F. Ventre C. Basios M. Kong H. Kanthan L. Martinez-Rego D. Wu F. Li L. (2020)," Cryptocurrency trading: a comprehensive survey", *King's College London & Turing Intelligence Technology Limited*, arXiv:2003.11352

Berensten A. & Schar F. (2018)," A short introduction to the world of cryptocurrencies", *Federal Reserve Bank of St. Louis Review*, First Quarter 2018, pp. 1-16

Wong Micheal C. S. (1997), "Abnormal stock returns following large one-day advances and declines: evidence from Asia-Pacific markets", *Kluwer Academic Publisher*, Financial engineering and Japanese Markets 4: pp 171-177

Wang K. Bellavitis C. DaSilva C. M. (2018), "An introduction to blockchain, cryptocurrency and initial coin offerings", *Social Science Research Network*, 3288059

Chevapatrakul T. & Mascia D. V. (2019), "Detecting overreaction in the Bitcoin market: a quantile autoregressive approach", *ELSEVIER*, Finance research letters, volume 30 September 2019 pp. 371-377

Houben R. & Snyers A. (2018) "Cryptocurrencies and blockchain. Legal context and implications for financial crime, money laundering and tax evasion", *European parliament – Policy Department for Economic, Scientific and Quality of Life Policies*, PE 619.024 - July 2018

IBM "Data science and machine learning" www.IBM.com [online]

J. J. Murphy (1999), "Technical analysis of the financial markets: A comprehensive guide to trading methods and applications", Penguin

Yahoo, Yahoo finance https://it.finance.yahoo.com [online]

J. W. Wilder (1978), "New concepts in technical trading systems", Trend Research

H. Markowitz (1952), "Portfolio selection", *The journal of finance*, vol. 7, no. 1, pp. 77–91

J. Golosova (2018), “Overview of the Blockchain Technology Cases”, Riga technology University

J. Liang, L. Li, W. Chen & D. Zeng (2019), “Towards an Understanding of Cryptocurrency: A Comparative Analysis of Cryptocurrency, Foreign Exchange, and Stock”, www.researchgate.net

S. Nakamoto (2008), “Bitcoin: A Peer-to-Peer Electronic Cash System” [Online]. Available: https://bitcoin.org/bitcoin.pdf.