Cryptocurrency Trading: A Comprehensive Survey

Fan Fang [a,*], Carmine Ventre[a], Michail Basios[b], Hoiliong Kong[b], Leslie Kanthan[b], Lingbo Li[b], David Martinez-Rego[b] and Fan Wu[b]

[a] *King's College London, UK*
[b] *Turing Intelligence Technology Limited, UK*

ARTICLE INFO

Keywords:

ABSTRACT

Since the inception of cryptocurrencies, an increasing number of financial institutions are getting involved in cryptocurrency trading. It is therefore important to summarise existing research papers and results on cryptocurrency trading. This paper provides a comprehensive survey of cryptocurrency trading research, by covering 118 research papers on various aspects of cryptocurrency trading (*e.g.*, cryptocurrency trading systems, bubble and extreme condition, prediction of volatility and return, crypto-assets portfolio construction and crypto-assets, technical trading and others). This paper also analyses datasets, research trends and distribution among research objects (contents/properties) and technologies, concluding with promising opportunities in cryptocurrency trading.

1. Introduction

Cryptocurrencies have experienced broad market acceptance and fast development despite their recent conception. Many hedge funds have began to include cryptocurrency-related assets into their portfolios and trading strategies. The academic community has similarly spent considerable efforts in researching cryptocurrency trading. This paper seeks to provide a comprehensive survey of the research on cryptocurrency trading, by which we mean any study aimed at facilitating and building strategies to trade cryptocurrencies.

As an emerging market and research direction, cryptocurrencies and cryptocurrency trading have seen considerable progress and a notable upturn in interest and activity. From Figure 1, we can see that over 85% of papers have appeared since 2018, demonstrating the emergence of cryptocurrency trading as new research direction in financial trading.

The literature is organised according to six different aspects of cryptocurrency trading:

- Cryptocurrency trading software systems (i.e., real-time trading system, turtle trading system, arbitrage trading system);
- Systematic trading including technical analysis, pairs trading and other systematic trading methods;
- Emergent trading technologies including econometrics methods, machine learning technology (machine learning model research, sentiment analysis, reinforcement learning and other machine learning research) and other emergent trading methods;
- Portfolio and cryptocurrency assets including research among cryptocurrency pairs and crypto-asset portfolio research;
- Market condition research including bubbles or crash analysis and extreme conditions;

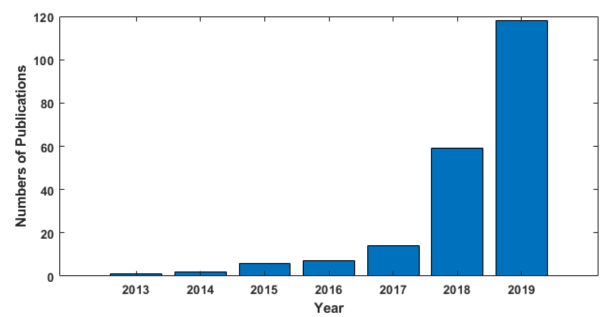

Figure 1: Cryptocurrency Trading Publications (cumulative) during 2013-2019

- Other cryptocurrency trading research.

Some papers may cover multiple aspects and will be surveyed for each (and accordingly mentioned in different sections).

We also summarise research distribution (among research properties, categories and research technologies). The distribution among properties and categories identifies classifications of research objectives and contents. The distribution among technologies identifies classifications of methodology or technical methods in researching cryptocurrency trading. Specifically, we subdivide research distribution among categories and technologies into statistical methods and machine learning technologies. Moreover, We identify datasets and opportunities (potential research directions) appeared in cryptocurrency trading area. To ensure that our survey is self-contained, we aim to provide sufficient material to adequately guide financial trading researchers who are interested in cryptocurrency trading.

There has been related work that discussed or partially surveyed the literature related to cryptocurrency trading. Kyriazis et al. [145] surveyed efficiency and profitable trading opportunities in cryptocurrency markets. Ahamad et al. [3] and Sharma et al. [194] gave a brief survey on cryptocurren-

fan.fang@kcl.ac.uk (Fan Fang)
ORCID(s): 0000-0002-5086-5614 (Fan Fang)

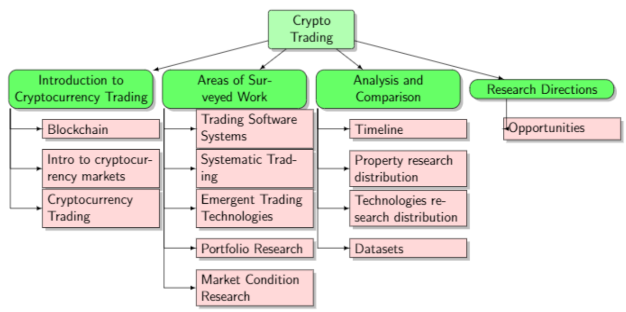

Figure 2: Tree structure of the contents in this paper

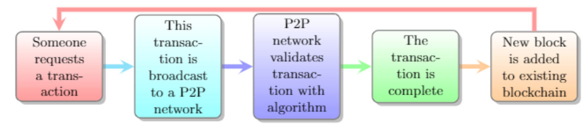

Figure 3: Workflow of Blockchain transaction

cies. Ujan et al. [166] gave a brief survey of cryptocurrency systems. To the best of our knowledge, no previous work has provided a comprehensive survey particularly focused on cryptocurrency trading.

In summary, the paper makes the following contributions:

Definition. The paper defines cryptocurrency trading and categorises it into cryptocurrency markets, cryptocurrency trading models and cryptocurrency trading strategies. The core content of this survey is trading strategies for cryptocurrencies.

Multidisciplinary Survey. The paper provides a comprehensive survey of 118 cryptocurrency trading papers, across different academic disciplines such as finance and economics, artificial intelligence and computer science.

Analysis. The paper analyses the research distribution, datasets and trends that characterise the cryptocurrency trading literature.

Horizons. The paper identifies challenges, promising research directions in cryptocurrency trading, aimed to promote and facilitate further research.

Figure 2 depicts the paper structure, which is informed by the review schema adopted. More details about this can be found in Section 4.

2. Cryptocurrency Trading

This section provides an introduction to cryptocurrency trading. We will discuss **Blockchain**, as the enabling technology, **cryptocurrency markets** and **cryptocurrency trading strategies**.

2.1. Blockchain

2.1.1. Blockchain Technology Introduction

Blockchain is an incorruptible digital ledger of economic transactions that can be used to record not just financial transactions but virtually everything of value [205]. In its simplest form, a Blockchain is a series of immutable data records with time stamps, which are managed by a cluster of machines that do not belong to any single entity. Each of these data *blocks* is protected by cryptographic principle and bound to each other in a *chain* (cf. Figure 3 for the workflow).

Cryptocurrencies like Bitcoin are made on a peer-to-peer network structure. Each peer has a complete history of all transactions, thus recording the balance of each account. For example, a transaction is a file that says "A pays X Bitcoins to B" that is signed by A using its private key. This is basic public key cryptography, but also the building block on which cryptocurrencies are based. After being signed, the transaction is broadcast on the network. When a peer discovers a new transaction, it checks to make sure that the signature is valid (this amounts to use the signer's public key, denoted as algorithm in Figure 3). If the verification is valid then the block is added to the chain; all other blocks added after it will "confirm" that transaction. For example, if a transaction is contained in block 502 and the length of the blockchain is 507 blocks, it means that the transaction has 5 confirmations (507-502) [191].

2.1.2. From Blockchain to Cryptocurrencies

Confirmation is a critical concept in cryptocurrencies; only miners can confirm transactions. Miners add blocks to the Blockchain; they take the transactions in the previous block and combine it with the hash of the previous block to get its hash, and then store the derived hash into the current block. Miners in Blockchain accept transactions, mark them as legitimate and broadcast them across the network. After the miner confirms the transaction, each node must add it to its database. In other words, it has become part of the Blockchain. Miners do this work to obtain cryptocurrency tokens, such as Bitcoin. In contrast to Blockchain, cryptocurrencies are related to the use of tokens based on distributed ledger technology. Any transaction involving purchase, sale, investment, etc. involves a Blockchain native token or sub-token. Blockchain is a platform that drives cryptocurrency and is a technology that acts as a distributed ledger for the network. The network creates the means of transaction and enable the transfer of value and information. Cryptocurrencies are the tokens used in these networks to send value and pay for these transactions. They can be thought of as tools on the Blockchain, and in some cases can also function as resources or utilities. Other times, they are used to digitize the value of assets. In summary, Cryptocurrencies are part of an ecosystem based on Blockchain technology.

2.2. Introduction of cryptocurrency market

2.2.1. What is cryptocurrency?

Cryptocurrency is a decentralised medium of exchange which uses cryptographic functions to conduct financial transactions [79]. Cryptocurrencies leverage the Blockchain technology to gain decentralisation, transparency, and immutability [162]. We have discussed above how Blockchain technology is used for cryptocurrencies.

In general, the security of cryptocurrencies is built on cryptography, not by people or trust [169]. For example, Bitcoin uses a method called "Elliptic Curve Cryptography" to ensure that transactions involving Bitcoin are secure [218]. Elliptic curve cryptography is a type of public key cryptography that relies on mathematics to ensure the security of transactions. When someone tries to hack this encryption scheme by brute force, it takes them one tenth the age of the universe to find a value match when trying 250 billion possibilities every second [103]. As a currency, cryptocurrency has the same properties as money. It has controlled supply. Most cryptocurrencies limit the supply of tokens. E.g. for Bitcoin, the supply will decrease over time and will reach its final quantity sometime around 2,140. All cryptocurrencies control the supply of tokens through a timetable encoded in the Blockchain.

One of the most important features of cryptocurrencies is that they do not involve financial institution intermediaries [110]. The absence of a "middleman" lowers transaction costs for traders. For comparison, if a bank's database is hacked or damaged, the bank will rely entirely on its backup to recover any information that is lost or compromised. With cryptocurrencies, even if part of the network is compromised, the rest will continue to be able to verify transactions correctly. Cryptocurrencies also have the important feature of not being controlled by any central authority [190]: the decentralised nature of the Blockchain makes cryptocurrencies theoretically immune to the old ways of government control and interference.

As of December 20, 2019, there exist 4,950 cryptocurrencies and 20,325 cryptocurrency markets; the market cap is around 190 billion dollars [67]. Figure 4 shows historical data on global market capitalisation and 24-hour trading volume [211]. The total market cap is calculated by aggregating the dollar market cap of all cryptocurrencies. From the figure, we can observe how cryptocurrencies experienced explosive growth in 2017 and a big bubble burst in early 2018. But in recent years, cryptocurrencies has remained relatively stable.

There are three mainstream cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), and Litecoin (LTC). Bitcoin was created in 2009 and had gained massive popularity. On October 31, 2008, an individual or group of individuals operating under the pseudonym Satoshi Nakamoto released the Bitcoin white paper and described it as: "A pure peer-to-peer version of electronic cash that can be sent online for payment from one party to another without going through a financial institution." [168] Launched by Vitalik Buterin in 2015, Ethereum is a special Blockchain with a special token called Ether (ETH symbol in exchanges). A very important feature of Ethereum is the ability to create new tokens on the Ethereum Blockchain. The Ethereum network went live on July 30, 2015, and pre-mined 72 million Ethereum. Litecoin is a peer-to-peer cryptocurrency created by Charlie Lee. It was created according to the Bitcoin protocol, but it uses a different hashing algorithm. Litecoin uses a memory-intensive proof-of-work algorithm, Scrypt. Scrypt allows consumer hardware (such as GPUs) to mine those coins.

Figure 4: Total Market Capitalization and Volume of cryptocurrency market, USD

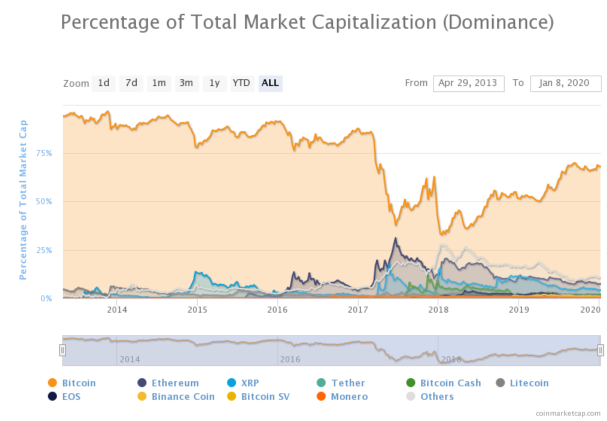

Figure 5: Percentage of Total Market Capitalisation [68]

Figure 5 shows percentages of total cryptocurrency market capitalisation; Bitcoin and Ethereum occupy the vast majority of the total market capitalisation (data collected on 8 Jan 2020).

2.2.2. Cryptocurrency Exchanges

A cryptocurrency exchange or digital currency exchange (DCE) is a business that allows customers to trade cryptocurrencies. Cryptocurrency exchanges can be market makers, usually using the bid-ask spread as a commission for services, or as a matching platform, by simply charging fees.

Table 1 shows the top or classical cryptocurrency exchanges according to the rank list, by volume, compiled on "nomics" website [173]. Chicago Mercantile Exchange (CME), Chicago Board Options Exchange (CBOE) and BAKKT

Table 1
Cryptocurrency exchanges Lists

Exchanges	Category	Supported currencies	Fiat Currency	Registration country	Regulatory authority
CME	Derivatives	BTC and Ethereum [61]	USD	USA [63]	CFTC [62]
CBOE	Derivatives	BTC [50]	USD	USA [49]	CFTC [51]
BAKKT (NYSE)	Derivatives	BTC [12]	USD	USA [13]	CFTC [12]
BitMex	Derivatives	12 cryptocurrencies [27]	USD	Seychelles [28]	-
Binance	Spot	98 cryptocurrencies [23]	EUR, NGN, RUB, TRY	Malta [158]	FATF [22]
Coinbase	Spot	28 cryptocurrencies [65]	EUR, GBP, USD	USA [33]	SEC [66]
Bitfinex	Spot	>100 cryptocurrencies [24]	EUR, GBP, JPY, USD	British Virgin Islands [25]	NYAG [26]
Bitstamp	Spot	5 cryptocurrencies [29]	EUR, USD	Luxembourg [30]	CSSF [31]
Poloniex	Spot	23 cryptocurrencies [186]	USD	USA [186]	-

(backed by New York Stock Exchange) are regulated cryptocurrency exchanges. Fiat currency data also comes from "nomics" website [173]. Regulatory authority and supported currencies of listed exchanges are collected from official websites or blogs.

2.3. Cryptocurrency Trading

2.3.1. *Definition*

Firstly we give a definition of *cryptocurrency trading*.

Definition 1. *Cryptocurrency trading is the act of buying and selling of cryptocurrencies with the intention of making a profit.*

The definition of cryptocurrency trading can be broken down into three aspects: object, operation mode and trading strategy. The object of cryptocurrency trading is the asset being traded, which is "cryptocurrency". The operation mode of cryptocurrency trading depends on the means of transaction in cryptocurrency market, which can be classified into "trading of cryptocurrency Contract for Differences (CFD)" (The contract between the two parties, often referred to as the "buyer" and "seller", stipulates that the buyer will pay the seller the difference between the present value of the asset and its value at the time of the contract [8]) and "buying and selling cryptocurrencies via an exchange". A trading strategy in cryptocurrency trading, formulated by an investor, is an algorithm that defines a set of predefined rules to buy and sell on cryptocurrency markets.

2.3.2. *Advantages of Trading Cryptocurrency*

The benefits of cryptocurrency trading include:

Drastic fluctuations. The volatility of cryptocurrencies are often likely to attract speculative interest and investors. The rapid fluctuations of intraday prices can provide traders with great money-earning opportunities, but it also includes more risk.

24-hour market. The cryptocurrency market is available 24 hours a day, 7 days a week because it is a decentralised market. Unlike buying and selling stocks and commodities, the cryptocurrency market is not traded physically from a single location. Cryptocurrency transactions can take place between individuals, in different venues across the world.

Near Anonymity. Buying goods and services using cryptocurrencies is done online and does not require to make one's own identity public. With increasing concerns over identity theft and privacy, cryptocurrencies can thus provide users with some advantages regarding privacy. Different exchanges have specific Know-Your-Customer (KYC) measures used to identify users or customers [2]. The KYC undertook in the exchanges allows financial institutions to reduce the financial risk while maximising the wallet owner's anonymity.

Peer-to-peer transactions. One of the biggest benefits of cryptocurrencies is that they do not involve financial institution intermediaries. As mentioned above, this can reduce transaction costs. Moreover, this feature might appeal users who distrust traditional systems. Over-the-counter (OTC) cryptocurrency markets offer, in this context, peer-to-peer transactions on the Blockchain. The most famous cryptocurrency OTC market is "LocalBitcoin [153]".

Programmable "smart" capabilities. Some cryptocurrencies can bring other benefits to holders, including limited ownership and voting rights. Cryptocurrencies may also include partial ownership interest in physical assets such as artwork or real estate.

3. Cryptocurrency Trading Strategy

Cryptocurrency trading strategy is the main focus of this survey. There are many trading strategies, which can be broadly divided into two main categories: technical and fundamental. They are similar in the sense that they both rely on quantifiable information that can be backtested against historical data to verify their performance. In recent years, a third kind of trading strategy, that we call quantitative, has received increasing attention. Such a trading strategy is similar to a technical trading strategy because it uses trading activity information on the exchange to make buying or selling decisions. Quantitative traders build trading strategies with quantitative data, which is mainly derived from price, volume, technical indicators or ratios to take advantage of inefficiencies in the market and are executed automatically by a trading software. Cryptocurrency market is different from traditional markets as there are more arbitrage opportunities, higher fluctuation and transparency. Due to these characteristics, most traders and analysts prefer using quantitative trading strategies in cryptocurrency markets.

3.1. Cryptocurrency Trading Software System

Software trading systems allow international transactions, process customer accounts and information, and accept and execute transaction orders [41]. A **cryptocurrency trading system** is a set of principles and procedures that are pre-programmed to allow trade between cryptocurrencies and between fiat currencies and cryptocurrencies. Cryptocurrency trading systems are built to overcome price manipulation, cybercriminal activities and transaction delays [17]. When developing a cryptocurrency trading system, we must consider capital market, base asset, investment plan and strategies [165]. Strategies are the most important part of an effective cryptocurrency trading system and they will be introduced below. There exist several cryptocurrency trading systems that are available commercially, for example Capfolio, 3Commas, CCXT, Freqtrade and Ctubio. From these cryptocurrency trading systems, investors can obtain professional trading strategy support, fairness and transparency from professional third-party consulting company and fast customer services.

3.2. Systematic Trading

Systematic Trading is a way to define trading goals, risk controls and rules. In general, systematic trading includes high frequency trading and slower investment types like systematic trend tracking. In this survey, we divide systematic cryptocurrency trading into technical analysis, pairs trading and others. Technical analysis in cryptocurrency trading is the act of using historical patterns of transaction data to assist a trader in assessing current and projecting future market conditions for the purpose of making profitable trades. Price and volume charts summarise all trading activity made by market participants in an exchange and affect their decisions. Some experiments showed that the use of specific technical trading rules allows generating excess returns, which is useful to cryptocurrency traders and investors in making optimal trading and investment decisions [101]. Pairs trading is a systematic trading strategy which consider two similar assets with slightly different spreads. If the spread widens, short the high stocks and buy the low stocks. When the spread narrows again to a certain equilibrium value, a profit is generated [82]. Papers shown in this section involve the analysis and comparison of technical indicator, pairs and informed trading, amongst other strategies.

3.3. Emergent Trading Technologies

Emergent trading strategies for cryptocurrency include strategies that are based on econometrics and machine learning technologies.

3.3.1. Econometrics on Cryptocurrency

Econometric methods apply a combination of statistical and economic theories to estimate economic variables and predict their values [216]. **Statistical models** use mathematical equations to encode information extracted from the data [135]. In some cases, statistical modeling techniques can quickly provide sufficiently accurate models [20]. Other methods might be used, such as sentiment-based prediction and long-and-short-term volatility classification based prediction [55]. The prediction of volatility can be used to judge the price fluctuation of cryptocurrencies, which is also valuable for the pricing of cryptocurrency related derivatives [130].

When studying cryptocurrency trading using econometrics, researchers apply statistical models on time-series data like generalised autoregressive conditional heteroskedasticity (GARCH) and BEKK (named after Baba, Engle, Kraft and Kroner, 1995 [84]) models to evaluate the fluctuation of cryptocurrencies [46]. A **linear statistical model** is a method to evaluate the linear relationship between prices and an explanatory variable [171]. When there exist more than one explanatory variable, we can model the linear relationship between explanatory (independent) and response (dependent) variables with multiple linear models. The common linear statistical model used in time-series analysis is autoregressive moving average (ARMA) model [59].

3.3.2. Machine Learning Technology

Machine learning is an efficient tool for developing Bitcoin and other cryptocurrency trading systems [161] because machine learning can predict or classify data relationships that are often non-linear and humans cannot observe. From the most basic perspective, machine learning is divided into two parts: input and goal. Input (data sources) is where knowledge of fundamental and technical analysis comes into play. We may divide the input into several groups of features, for example, those based on Economic indicators (such as, gross domestic product indicator, interest rates,etc.), Social indicators (Google Trends, Twitter, etc.), Technical indicators (price, volume,etc.) and other Seasonal indicators (time of day, day of week, etc.). Goal reflects the final result one wants from the machine learning model. We can distinguish goals in prediction or classification into numeric (e.g., price) and categorical (e.g., trend) options. The machine learning model will be trained by using the input data (sometimes called in-sample) and will attempt to *generalise* patterns therein to unseen (out-of-sample) data to (approximately) achieve the goal. Clearly, traders will need to extract trading signals from these goals. We can also apply machine learning and statistical approaches, such as, cross validation, to validate the model before we actually use it to make predictions. In machine learning, this is typically called “validation”. The process of using machine learning technology to predict cryptocurrency is shown in Figure 6.

Basically we can classify Machine Learning technology into three categories: Supervised learning, Unsupervised learning and Reinforcement learning. **Supervised learning** is used to derive a predictive function from labeled training data and labeled training data means that each training instance includes inputs and expected outputs. **Unsuper-**

Figure 6: Process of machine learning in predicting cryptocurrency

vised learning is to infer conclusions from unlabeled training data and it can be used during exploratory data analysis to discover hidden patterns or to group data according to any pre-defined similarity metrics. **Reinforcement learning** focuses on how software agents act in an environment to maximize some cumulative return. In financial sector, some trading challenges can be expressed as a game in which an agent can be designed to maximize returns.

The use of machine learning in cryptocurrency trading research encompasses sentiment analysis, machine learning model research, reinforcement learning, comparison between machine technologies and classical statistical methods, etc. Further concrete examples are shown in later section.

3.4. Portfolio Research

Portfolio theory advocates a diversification of investments to maximize returns for a given level of risk by allocating assets strategically. The celebrated mean-variance optimisation is a prominent example of this approach [159]. Generally, **crypto asset** denotes a digital asset (i.e., cryptocurrencies and derivatives). There are some common ways to build a diversified portfolio in crypto assets. The first method is to diversify across markets, which is to mix a wide variety of investments within a portfolio of cryptocurrency market. The second method is to consider the industry sector, which is to avoid investing too much money in any one category. Diversified investment of portfolio in cryptocurrency market includes portfolio across cryptocurrencies [152] and portfolio across global market including stocks and futures [123].

3.5. Market Condition Research

Market condition research appears especially important for cryptocurrencies. A **financial bubble** is a significant increase in the price of an asset without changes in its intrinsic value [39]. Many experts pinpoint a cryptocurrency bubble in 2017 when the prices of cryptocurrencies grew by 900%. In 2018, Bitcoin faced a collapse in its value. This significant fluctuation inspired researchers to study bubbles and extreme conditions in cryptocurrency trading.

4. Paper Collection and Review Schema

The section introduces the scope and approach of our paper collection, a basic analysis, and the structure of our survey.

Table 2
Survey scope table

Trading (bottom up)	Trading System
	Prediction (return) Prediction (volatility)
	Technical trading methods
Risk management	Bubble and extreme condition
	Porfolio and Cryptocurrency asset
Others	

4.1. Survey Scope

We adopt a bottom up approach to the research in cryptocurrency trading, starting from the system up to risk management techniques. For the underlying trading system, we focus on the optimisation of its structure and improvements of computer science technologies. At a higher level, researchers use various models to predict return or volatility in cryptocurrency markets, useful to generate trading signals. At the top level, researchers discuss technical trading methods when trading in real cryptocurrency market. Bubbles and extreme conditions are hot topics in cryptocurrency trading because, as discussed above, these markets have shown to be highly volatile (whilst volatility went down after crashes). Portfolio and cryptocurrency asset management are effective methods to control risk. We group these two areas in risk management research. Other papers included in this survey include topics like pricing rules, dynamic market analysis, regulatory implications, and so on. Table 2 shows the general scope of cryptocurrency trading included in this survey.

Since many trading strategies and methods in cryptocurrency trading are closely related to stock trading, some researchers migrate or use the research results for the latter to the former. When conducting this research, we only consider those papers whose research focus on cryptocurrency markets or a comparison of trading in those and other financial markets.

Specifically, we apply the following criteria when collecting papers related to cryptocurrency trading:

1. The paper introduces or discusses the general idea of cryptocurrency trading or one of the related aspects of cryptocurrency trading.
2. The paper proposes an approach, study or framework that targets optimised efficiency or accuracy of cryptocurrency trading.
3. The paper compares different approaches or perspectives in trading cryptocurrency.

By "cryptocurrency trading" here, we mean one of the terms listed in Table 2 and discussed above.

Some researchers gave a brief survey of cryptocurrency [3, 194], cryptocurrency systems [166] and cryptocurrency trading opportunities [145]. These surveys are rather limited in scope as compared to ours, which also includes a discussion on the latest papers in the area; we remark that this is a fast moving research field.

Table 3
Paper query results. #Hits, #Title, and #Body denote the number of papers returned by the search, left after title filtering, and left after body filtering, respectively.

Key Words	#Hits	#Title	#Body
[Crypto] + Trading	555	32	29
[Crypto] + Trading System	4	3	2
[Crypto] + Prediction	26	14	13
[Crypto] + Trading Strategy	22	9	8
[Crypto] + Risk Management / [Crypto] + Portfolio	120	14	14
Query	-	-	66
Snowball	-	-	52
Overall	-	-	118

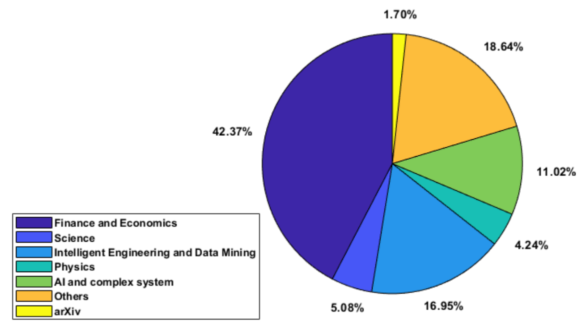

Figure 7: Publication Venue Distribution

4.2. Paper Collection Methodology

To collect the papers in different areas or platforms, we used keyword searches on Google Scholar and arXiv, two of the most popular scientific databases. The keywords used for searching and collecting are listed below. [Crypto] means cryptocurrency market, which is our research interest because methods might be different among different markets. We conducted 6 searches across the two repositories before October 15, 2019.

- [Crypto] + Trading
- [Crypto] + Trading system
- [Crypto] + Prediction
- [Crypto] + Trading strategy
- [Crypto] + Risk Management
- [Crypto] + Portfolio

To ensure a high coverage, we adopted the so-called **snowballing** [222] method on each paper found through these keywords. We checked papers added from snowballing methods that satisfy the criteria introduced above, until we reached closure.

4.3. Collection Results

Table 3 shows the details of the results from our paper collection. Keyword searches and snowballing resulted in 118 papers across the six research areas of interest in Section 4.1.

Figure 7 shows distribution of papers published at different research sites. Among all the papers, 42.37% papers are published in Finance and Economics venues such as Journal of Financial Economics (JFE), Cambridge Centre for Alternative Finance (CCAF), Finance Research Letters, Centre for Economic Policy Research (CEPR) and Journal of Risk and Financial Management (JRFM); 5.08% papers are published in Science venues such as Public Library Of Science one (PLOS one), Royal Society open science and SAGE; 16.95% papers are published in Intelligent Engineering and Data Mining venues such as Symposium Series on Computational Intelligence (SSCI), Intelligent Systems Conference (IntelliSys), Intelligent Data Engineering and Automated Learning (IDEAL) and International Conference on Data Mining (ICDM); 4.24% papers are published in Physics venues such as Physica A and International Cosmetic Physicians Society (ICPS); 11.02% papers are published in AI and complex system venues such as Complexity and International Federation for Information Processing (IFIP); 18.64% papers are published in Others venues which contains independently published papers and dissertations; 1.70% papers are published on arXiv. The distribution of different venues shows that cryptocurrency trading is mostly published in Finance and Economics venues, but with a wide diversity otherwise.

4.4. Survey Organisation

We discuss the contributions of the collected papers and a statistical analysis of these papers in the remainder of the paper, according to Table 4.

The papers in our collection are organised and presented from six angles. We introduce the work about several different cryptocurrency trading software systems in Section 5. Section 6 introduces systematic trading applied to cryptocurrency trading. In Section 7, we introduce some emergent trading technologies including econometrics on cryptocurrencies, machine learning technologies and other emergent trading technologies in cryptocurrency market. Section 8 introduces research on cryptocurrency pairs and related factors and crypto-asset portfolios research. In Section 9 we discuss cryptocurrency market condition research, including bubbles, crash analysis, and extreme conditions. Section 10 introduces other research included in cryptocurrency trading not covered above.

We would like to emphasize that the six headings above focus on a particular aspect of cryptocurrency trading; we give a complete organisation of the papers collected under each heading. This implies that those papers covering more than one aspect will be discussed in different sections, once from each angle.

We analyse and compare the number of research papers on different cryptocurrency trading properties and technologies in Section 11, where we also summarise the datasets and the timeline of research in cryptocurrency trading.

We build upon this review to conclude in Section 12 with some opportunities for future research.

Table 4
Review Schema

Classification	Sec	Topic
Cryptocurrency Trading Software System	5.1	Trading Infrastructure System
	5.2	Real-time Cryptocurrency Trading System
	5.3	Turtle trading system in Cryptocurrency market
	5.4	Arbitrage Trading Systems for Cryptocurrencies
	5.5	Comparison of three cryptocurrency trading systems
Systematic Trading	6.1	Technical Analysis
	6.2	Pairs Trading
	6.3	Others
Emergent Trading Technologies	7.1	Econometrics on cryptocurrency
	7.2	Machine learning technology
	7.3	Others
Portfolio and Cryptocurrency Assets	8.1	Research among cryptocurrency pairs and related factors
	8.2	Crypto-asset portfolio research
Market condition research	9.1	Bubbles and crash analysis
	9.2	Extreme condition
Others	10	Others related to Cryptocurrency Trading
Summary Analysis of Literature Review	11.1	Timeline
	11.2	Research distribution among properties
	11.3	Research distribution among categories and technologies
	11.4	Datasets used in cryptocurrency trading

5. Cryptocurrency Trading Software Systems

5.1. Trading Infrastructure Systems

Following the development of computer science and cryptocurrency trading, many cryptocurrency trading systems/bots have been developed. Table 5 compares the cryptocurrency trading systems existing in the market. The table is sorted based on URL types (GitHub or Official website) and GitHub stars (if appropriate).

Capfolio is a proprietary payable cryptocurrency trading system which is a professional analysis platform and has a advanced backtesting engine [42]. It supports five different cryptocurrency exchanges.

3 Commas is a proprietary payable cryptocurrency trading system platform which can take profit and stop loss orders at the same time [1]. Twelve different cryptocurrency exchanges are compatible with this system.

CCXT is a cryptocurrency trading system with a unified API out of the box and optional normalized data, and supports many Bitcoin / Ether / Altcoin exchange markets and merchant APIs. Any trader or developer can create a trading strategy based on this data and access public transactions through the APIs [52]. The CCXT library is used to connect and trade with cryptocurrency exchanges and payment processing services worldwide. It provides quick access to market data for storage, analysis, visualisation, indicator development, algorithmic trading, strategy backtesting, automated code generation and related software engineering. It is designed for coders, skilled traders, data scientists and financial analysts to build trading algorithms. Current CCXT features include:

I. Support for many cryptocurrency exchanges;
II. Fully implemented public and private APIs;
III. Optional normalized data for cross-exchange analysis and arbitrage;
IV. Out-of-the-box unified API, very easy to integrate.

Blackbird Bitcoin Arbitrage is a C++ trading system that automatically executes long / short arbitrage between Bitcoin exchanges. It can generate market-neural strategies which do not transfer funds between exchanges [32]. The motivation behind Blackbird is to naturally profit from these temporary price differences between different exchanges while being market neutral. Unlike other Bitcoin arbitrage systems, Blackbird does not sell but actually short sells Bitcoin on the short exchange. This feature offers two important advantages. Firstly, the strategy is always market agnostic: fluctuations (rising or falling) in the Bitcoin market will not affect the strategy returns. This eliminates the huge risks of this strategy. Secondly, this strategy does not require transferring funds (USD or BTC) between Bitcoin exchanges. Buy and sell transactions are conducted in parallel on two different exchanges. There is no need to deal with transmission delays.

StockSharp is an open source trading platform for trading at any market of the world including 48 cryptocurrency exchanges [200]. It has a free C# library and free trading charting application. Manual or automatic trading (algorithmic trading robot, regular or HFT) can be run on this platform. StockSharp consists of five components that offer different features:

I. S#.Designer - Free universal algorithm strategy app, easy to create strategies;
II. S#.Data - free software that can automatically load and store market data;
III. S#.Terminal - free trading chart application (trading terminal);
IV. S#.Shell - ready-made graphics framework that can be changed according to needs and has fully open source in C#;

V. S#.API - a free C# library for programmers using Visual Studio. Any trading strategies can be created in S#.API.

Freqtrade is a free and open source cryptocurrency trading robot system written in Python. It is designed to support all major exchanges and is controlled by telegram. It contains backtesting, mapping and money management tools, and strategy optimization through machine learning [93]. Freqtrade has following features:

I. Persistence: Persistence is achieved through sqlite technology;
II. Strategy optimization through machine learning: Use machine learning to optimize your trading strategy parameters with real trading data;
III. Marginal Position Size: Calculates winning rate, risk-return ratio, optimal stop loss and adjusts position size, and then trades positions for each specific market;
IV. Telegram management: use telegram to manage the robot.
V. Dry run: Run the robot without spending money;

CryptoSignal is a professional technical analysis cryptocurrency trading system [75]. Investors can track over 500 coins of Bittrex, Bitfinex, GDAX, Gemini and more. Automated technical analysis include momentum, RSI, Ichimoku Cloud, MACD etc. The system gives alerts including Email, Slack, Telegram etc. CryptoSignal has two primary features. First of all, it offers modular code for easy implementation of trading strategies; Secondly, it is easy to install with Docker.

Ctubio is a C++ based low latency (high frequency) cryptocurrency trading system [76]. This trading system can place or cancel orders through supported cryptocurrency exchanges in less than a few milliseconds. Moreover, it provides a charting system that can visualise the trading account status including trades completed, target position for fiat currency, etc.

Catalyst is a analysis and visualization of cryptocurrency trading system [48]. It makes trading strategies easy to express and trace back historical data (daily and minute resolution), providing analysis and insights into the performance of specific strategies. Catalyst allows users to share and organize data and build profitable, data-driven investment strategies. Catalyst not only supports the trading execution but also offers historical price data of all crypto assets (from minute to daily resolution). Catalyst also has backtesting and real-time trading capabilities, which enables user to seamlessly transit between the two different trading modes. Lastly, Catalyst integrates statistics and machine learning libraries (such as matplotlib, scipy, statsmodels and sklearn) to support the development, analysis and visualization of the latest trading systems.

Golang Crypto Trading Bot is a Go based cryptocurrency trading system [102]. Users can test the strategy in sandbox environment simulation. If simulation mode is enabled, a fake balance for each coin must be specified for each exchange.

5.2. Real-time Cryptocurrency Trading Systems

Amit et al. [17] developed a real-time Cryptocurrency Trading System. A real-time cryptocurrency trading system is composed of clients, server and database. Traders use a web-application to login the server to buy/sell crypto assets. The server collects cryptocurrency market data by creating a script which uses the Coinmarket API. Finally, the database collects balances, trades and order book information from server. Data in database is the copy of master data. Authors used login authentication, IP address validation, session-hashing-salt and user document verification to protect the security of this trading system. The authors tested the system with an experiment that demonstrates user-friendly experiences for traders in cryptocurrency exchange platform.

5.3. Turtle trading system in Cryptocurrency market

The original Turtle Trading system is a trend following trading system developed in the 1970's. The idea is to generate buy and sell signals on a stock for short-term and long-term breakouts and its cut-loss condition which is measured by Average true range (ATR) [127]. The trading system will adjust the size of assets based on their volatility. Essentially, if a turtle accumulates a position in a highly volatile market, it will be offset by a low volatility position. Extended Turtle Trading system is improved with smaller time interval spans and introduces a new rule by using exponential moving average (EMA). Three EMA values are used to trigger "buy" signal: 30EMA (Fast), 60EMA (Slow), 100EMA (Long). The author of [127] performed backtesting and comparing both trading systems (Original Turtle and Extended Turtle) on 8 prominent cryptocurrencies. Through the experiment, Original Turtle Trading System achieved 18.59% average net profit margin (percentage of net profit over total revenue) and 35.94% average profitability (percentage of winning trades over total numbers of trades) in 87 trades through nearly one year. Extended Turtle Trading System achieved 114.41% average net profit margin and 52.75% average profitability in 41 trades through the same time interval. This research showed how Extended Turtle Trading System compared can improve over Original Turtle Trading System in trading cryptocurrencies.

5.4. Arbitrage Trading Systems for Cryptocurrencies

Christian [178] introduced arbitrage trading systems for cryptocurrencies. Arbitrage trading aims to spot the differences in price that can occur when there are discrepancies in the levels of supply and demand across multiple exchanges. As a result, a trader could realise a quick and low-risk profit by buying from one exchange and selling at a higher price on a different exchange. Arbitrage trading signals are caught by automated trading software. The technical differences between data sources impose a server process to be organised for each data source. Relational databases and SQL are a reliable solution due to large amount of relational data.

Table 5
Comparison of existing cryptocurrency trading systems. #Exchange, Language, and #Popularity denote the number of the exchanges that are supported by this software, programming language used, and the popularity of the software (number of the stars in Github).

Name	Features	#Exchange	Language	Open-Source	URL	#Popularity
Capfolio	Professional analysis platform, Advanced backtesting engine	5	Not mentioned	No	Official website [42]	
3 Commas	Simultaneous take profit and stop loss orders	12	Not mentioned	No	Official website [1]	
CCXT	An out of the box unified API, optional normalized data	10	JavaScript / Python / PHP	Yes	GitHub [52]	13k
BlackBird	Strategy is market-neutral strategy not transfer funds between exchanges	8	C++	Yes	GitHub [32]	4.7k
StockSharp	Free C# library, free trading charting application	48	C#	Yes	GitHub [200]	2.6k
Freqtrade	Strategy Optimization by machine learning, Calculate edge position sizing	2	Python	Yes	GitHub [93]	2.4k
CryptoSignal	Technical analysis trading system	4	Python	Yes	GitHub [75]	1.9k
Ctubio	Low latency	1	C++	Yes	GitHub [76]	1.7k
Catalyst	Analysis and visualization of system seamless transition between live and back-testing	4	Python	Yes	GitHub [48]	1.7k
GoLang	Sandbox environment simulation	7	Go	Yes	GitHub [102]	277

The author used the system to catch arbitrage opportunities on 25 May 2018 among 787 cryptocurrencies on 7 different exchanges. The research paper [178] listed the best ten trading signals made by this system from 186 available found signals. The results showed that the system caught trading signal of "BTG-BTC" to get a profit up to 495.44% when arbitraging to buy in Cryptopia exchange and sell in Binance exchange. Another three well traded arbitrage signals (profit expectation around 20% mentioned by the author) were found on 25 May 2018. Arbitrage Trading Software System introduced in that paper presented general principles and implementation of arbitrage trading system in cryptocurrency market.

5.5. Comparison of three cryptocurrency trading systems

Real-time trading system has real-time function in collecting data and generating trading algorithms. Turtle trading system and arbitrage trading system have shown a sharp contrast in their profit and risk behavior. Using Turtle trading system in cryptocurrency markets got high return with high risk. Arbitrage trading system is inferior in terms of revenue but also has a lower risk. One feature that turtle trading system and arbitrage trading system have in common is they performed well in capturing alpha.

6. Systematic Trading

6.1. Technical Analysis

Many researchers focused on technical indicators (patterns) analysis for trading on cryptocurrency markets. Examples of studies with this approach include "Turtle Soup pattern strategy" [206], "Nem (XEM) strategy" [209], "Amazing Gann Box strategy" [207], "Busted Double Top Pattern strategy" [208], and "Bottom Rotation Trading strategy" [210]. Table 6 shows the comparison among these five classical technical trading strategies using technical indicators. "Turtle soup pattern strategy" [206] used 2-daybreakout of price in predicting price trends of cryptocurrencies. This strategy is a kind of chart trading pattern. "Nem (XEM) strategy" combined Rate of Change (ROC) indicator and Relative Strength Index (RSI) in predicting price trends [209]. "Amazing Gann Box" predicted exact points of increase and decrease in Gann Box which are used to catch explosive trends of cryptocurrency price [207]. Technical analysis tools such as candlestick and boxcharts with Fibonacci Retracement based on golden ratio are used in this technical analysis. Fibonacci Retracement uses horizontal lines to indicate where possible support and resistance levels are in the market. "Busted Double Top Pattern" used Bearish reversal trading pattern which generates a sell signal to predict price trends [208]. "Bottom Rotation Trading" is a technical analysis method which picks the bottom before the reversal happens. This strategy used price chart pattern and box chart as technical analysis tools.

Sungjoo et al. [107] investigated using genetic programming (GP) to find attractive technical patterns in the cryptocurrency market. Over 12 technical indicators including Moving Average (MA) and Stochastic oscillator were used in experiments; adjusted gain, match count, relative market pressure and diversity measures have been used to quantify the attractiveness of technical patterns. With extended experiments, the GP system is shown to find successfully attractive technical patterns, which are useful for portfolio optimization. Hudson et al. [115] applied almost 15,000 technical trading rules (classified into MA rules, filter rules, support resistance rules, oscillator rules and channel breakout rules). This comprehensive study found that technical trading rules provide investors with significant predictive power and profitability. Shaen et al. [71] analysed various technical trading rules in the form of the moving average-oscillator and trading range break-out strategies to generate higher returns in cryptocurrency markets. By using one-minute dollar denominated Bitcoin close-price data, the backtest showed variable-length moving average (VMA) rule per-

Table 6
Comparison among five classical technical trading strategies

Technical trading strategy	Core Methods	Tecchnical tools/patterns
Turtle Soup pattern [206]	2-daybreakout of price	Chart trading patterns
Nem (XEM) [209]	Price trends combined ROC & RSI	Rate of Change indictor (ROC) Relative strength index (RSI)
Amazing Gann Box [207]	Predict exact points of rises and falls in Gann Box (catch explosive trends)	Candlestick, boxcharts with Fibonacci Retracement
Busted Double Top Pattern [208]	Bearish reversal trading pattern that generates a sell signal	Price chart pattern
Bottom Rotation Trading [210]	Pick the bottom before the reversal happens	Price chart pattern, box chart

forms best considering it generates most useful signals in high frequency trading.

6.2. Pairs Trading

Pairs trading is a trading strategy that attempts to exploit mean-reversion between the prices of certain securities. Miroslav [91] investigated applicability of standard pairs trading approaches on cryptocurrency data with the benchmarks of Gatev et al. [100]. The pairs trading strategy is constructed in two steps. Firstly, suitable pairs with a stable long-run relationship are identified. Secondly, the long-run equilibrium is calculated and pairs trading strategy is defined by the spread based on the values. The research also extended intra-day pairs trading using high frequency data. Overall, the model was able to achieve 3% monthly profit in Miroslav's experiments [91]. Broek [38] applied pairs trading based on cointegration in cryptocurrency trading and 31 pairs were found to be significantly cointegrated (within sector and cross-sector). By selecting four pairs and testing over a 60-day trading period, the pairs trading strategy got its profitability from arbitrage opportunities, which rejected the Efficient-market hypothesis (EMH) for the cryptocurrency market.

6.3. Others

Other systematic trading methods in cryptocurrency trading mainly include informed trading. Using USD / BTC exchange rate trading data, Feng et al. [90] found evidence of informed trading in the Bitcoin market in that quantiles of the order sizes of buyer-initiated (seller-initiated) orders are abnormally high before large positive (negative) events, compared to the quantiles of seller-initiated (buyer-initiated) orders; this study adopts a new indicator inspired by the volume imbalance indicator [81]. The evidence of informed trading in Bitcoin market suggests that investors profit on their private information when they get information before it is widely available.

7. Emergent Trading Technologies

7.1. Econometrics on cryptocurrency

Copula-quantile causality analysis and Granger-causality analysis are methods to investigate causality in cryptocurrency trading analysis. Bouri et al. [35] applied a copula-quantile causality approach on volatility in the cryptocurrency market. The approach of the experiment extended Copula-Granger-causality in distribution (CGCD) method of Lee and Yang [149] in 2014. The experiment constructed two tests of CGCD using copula functions. The parametric test employed six parametric copula functions to discover dependency density between variables. The performance matrix of these functions varies with independent copula density. Three distribution regions are the focus of this research: left tail (1%, 5%, 10% quantile), central region (40%, 60% quantile and median) and right tail (90%, 95%, 99% quantile). The study provided significant evidence of Granger causality from trading volume to the returns of seven large cryptocurrencies on both left and right tails. Badenhorst [10] attempted to reveal whether spot and derivative market volumes affect Bitcoin price volatility with Granger-causality method and ARCH (1,1). The result shows spot trading volumes have a significant positive effect on price volatility while relationship between cryptocurrency volatility and derivative market is uncertain.

Several econometrics methods in time series research, such as wavelet analysis, GARCH and BEKK, have been used in the literature on cryptocurrency trading. Maurice et al [176] applied wavelet time-scale persistence in analysing returns and volatility in cryptocurrency markets. The experiment examined long-memory and market efficiency characteristics in cryptocurrency markets using daily data for more than two years. The authors employed a log-periodogram regression method in researching stationarity in cryptocurrency market and used ARFIMA-FIGARCH class of models in examining long-memory behaviour of cryptocurrencies across time and scale. In general, experiments indicated that heterogeneous memory behaviour existed in eight cryptocurrency markets using daily data over the full-time period and across scales (August 25, 2015 to March 13, 2018). Conrad et al. [70] used the GARCH-MIDAS model to extract long and short-term volatility components of Bitcoin market. The technical details of this model decomposed the conditional variance into low-frequency and high-frequency component. The results identified that S&P 500 realized volatility has a negative and highly significant effect on long-term Bitcoin volatility and S&P 500 volatility risk premium has a significantly positive effect on long-term Bitcoin volatility.

Some researchers focused on long memory methods for volatility in cryptocurrency markets. Long memory methods focused on long-range dependence and significant long-term correlations among fluctuations on markets. Chaim et al. [54] estimated a multivariate stochastic volatility model with discontinuous jumps in cryptocurrency markets. The results showed that permanent volatility appears to be driven by major market developments and popular interest level. Caporale et al. [43] examined persistence in cryptocurrency market by Rescaled range (R/S) analysis and fractional integration. The results of the study indicated that the market is persistent (there is a positive correlation between its past and future values) and that its level changes over time. Khuntin et al. [136] applied the adaptive market hypothesis (AMH) in the predictability of Bitcoin evolving returns. The consistent test of Dominguez and Lobato [78], generalized spectral (GS) of Escanciano and Velasco [86] are applied in capturing time-varying linear and nonlinear dependence in bitcoin returns. The results verified Evolving Efficiency in Bitcoin price changes and evidence of dynamic efficiency in line with AMH's claims.

Katsiampa et al. [133] applied three pair-wise bivariate BEKK models to examine the conditional volatility dynamics along with interlinkages and conditional correlations between three pairs of cryptocurrencies in 2018. More specifically, the BEKK-MGARCH methodology also captured cross-market effects of shocks and volatility, which are also known as shock transmission effects and volatility spillover effects. The experiment found evidence of bi-directional shock transmission effects between Bitcoin and both Ether and Litcoin. In particular, bi-directional shock spillover effects are identified between three pairs (Bitcoin, Ether and Litcoin) and time-varying conditional correlations exist with positive correlations mostly prevailing. In 2019, Katsiampa [132] further researched an asymmetric diagonal BEKK model to examine conditional variances of five cryptocurrencies that are significantly affected by both previous squared errors and past conditional volatility. The experiment tested the null hypothesis of the unit root against stationarity hypothesis. Once stationarity is ensured, ARCH LM is tested for ARCH effects to examine requirement of volatility modelling in return series. Volatility co-movements in among cryptocurrency pairs are also tested by multivariate GARCH model. The results confirmed the non-normality and heteroskedasticity of price returns in cryptocurrency markets. The finding also identified the effects of cryptocurrencies' volatility dynamics due to major news. Hultman [116] set out to examine GARCH (1,1), bivariate-BEKK (1,1) and a standard stochastic model to forecast the volatility of Bitcoin. A rolling window approach is used in these experiments. Mean absolute error (MAE), Mean squared error (MSE) and Root-mean-square deviation (RMSE) are three loss criteria adopted to evaluate the degree of error between predicted and true values. The result shows the following rank of loss functions: GARCH (1,1) > bivariate-BEKK (1,1) > Standard stochastic for all the three different loss criteria; in other words, GARCH(1,1) appeared best in predicting the volatility of Bitcoin. Wavelet time-scale persistence analysis is also applied in prediction and research of volatility in cryptocurrency markets [176]. The results showed that information efficiency (efficiency) and volatility persistence in cryptocurrency market are highly sensitive to time scales, measures of returns and volatility, and institutional changes. Adjepong et al. [176] connected with a similar research of Corbet et al. [74] and showed that GARCH is quicker than BEKK to absorb new information regarding the data.

7.2. Machine Learning Technology

Machine learning technology constructs computer algorithms that automatically improve themselves by finding patterns in existing data without explicit instructions [113]. The rapid development of machine learning in recent years has promoted its application to cryptocurrency trading, especially in prediction of cryptocurrency returns.

7.2.1. Common Machine Learning Technology in this survey

Some machine learning technologies are applied in cryptocurrency trading. We distinguish these machine learning technologies by type/function: classification, clustering, regression, deep learning, reinforcement learning and others.

Classification Algorithms. Classification in machine learning is a technique that can classify data into different categories as needed, where we can assign labels to each category (e.g., up and down). Naive Bayes (NB) [189], Support Vector Machine (SVM) [219], K-Nearest Neighbours (KNN) [219], Decision Tree (DT) [94], Random Forest (RF) [151] and Gradient Boosting (GB) [96] algorithms are used in cryptocurrency trading based on papers we collected. NB is a probabilistic classifier based on Bayes' theorem with strong (naive) independence assumptions between features [189]. SVM is supervised learning model combined with associated learning algorithms [228]. The SVM training algorithm builds a model that assigns new examples to one category or another, making it a non-probabilistic binary linear classifier [219]. KNN is a case-based learning or lazy learning algorithm, where the function is only approximated locally, and all calculations will be postponed to classification [219]. DT is a decision support tool algorithm that uses a tree-like decision graph or model and its possible consequences [94]. RF is an ensemble learning method. The algorithm operates by constructing a large number of decision trees during training and outputting the classes as a class pattern (classification) or mean prediction (regression) [151]. GB produces a prediction model in the form of an ensemble of weak prediction models, a subclass of machine learning for prediction [96].

Clustering Algorithms. Clustering is a machine learning technique that involves grouping data points [121]. Given a set of data points, we can use a clustering algorithm to classify each data point into a specific group. K-Means is one of the clustering algorithms used in cryptocurrency trading according to the papers we collected (actually, K-Means is the only one used in the papers collected). K-Means is a vector quantization used for clustering analysis in data mining. K-means stores the k-centroids used to define the clusters; a point is considered to be in a particular cluster if it is closer to the cluster's centroid than any other centroid [217].

Regression Algorithms. Regression is a statistical measurement that is used to predict a continuous value [143]. Linear Regression (LR) and Scatterplot Smoothing are common techniques used in solving regression problems in cryptocurrency trading. LR is a linear method used to model the relationship between a scalar response (or dependent variable) and one or more explanatory variables (or independent variables) [143]. Scatterplot Smoothing is a technology to fit functions through scatter plots to best represent relationships between variables [95].

Deep Learning Algorithms. Deep learning is a modern take on artificial neural networks (ANNs) [229], made possible by the advances in computational power. An ANN is a computational system inspired by the fuzzy neural networks that make up the animal's brain. The system "learns" to perform tasks including prediction by considering examples. Deep learning's superior accuracy comes from high computational complexity cost. Deep learning algorithms are currently the basis for many modern artificial intelligence applications [204]. Convolutional neural networks (CNNs) [147], Recurrent neural networks (RNNs) [163], Gated recurrent units (GRUs) [60], Multilayer perceptron (MLP) and Long short-term memory (LSTM) [57] networks are most common deep learning technologies used in cryptocurrency trading. A CNN is a specific type of artificial neural network that uses perceptrons (a machine learning neuron or unit) for supervised learning to analyse data. CNNs are suitable for image processing and natural language processing. An attempt to use CNNs in cryptocurrency is [126]. An RNN is a type of artificial neural network in which connections between nodes form a directed graph along a time series. Consequently, the structure of RNNs makes them suitable for processing time-series data [163]. LSTM [57] is a particular RNN architecture for deep learning. LSTMs are usually superior to RNNs on financial time-series problems because they have the ability to selectively remember patterns for a long time. A GRU [60] is an improved version of the standard RNN which solves vanishing gradients problem, a technical issue to do with training ANNs. MLP is a class of feedforward ANN which is trained with a supervised learning technique called backpropagation (BP).

Reinforcement Learning Algorithms. Reinforcement learning (RL) is an area of machine learning leveraging the idea that software agents act in the environment to maximize cumulative rewards [203]. Deep Q-Learning (DQN) [105] and Deep Boltzmann Machine (DBM) [192] are common technologies used in cryptocurreny trading using RL. Deep Q learning uses neural networks to approximate Q-value functions. A state is given as input, and Q values for all possible actions are generated as outputs [105]. DBM is a type of binary paired Markov random field (undirected probability graphical model) with multiple layers of hidden random variables. It is a network of randomly coupled random binary units [192].

Others. Another machine learning technology used in cryptocurrency trading is Seq2seq; this network has a so-called Encoder–Decoder architecture [223]. Seq2seq is created for solving natural language processing problems, but has been applied it in cryptocurrency trend predictions in [199].

7.2.2. Research on Machine Learning Models

With the development of machine learning, technical indicators have been used as input features. Nakano et al. [168] explored Bitcoin intraday technical trading based on ANNs for return prediction. The experiment obtained high frequency price and volume data (time interval of data is 15min) of Bitcoin from a cryptocurrency exchange. An ANN predicts the price trends (up and down) in next period from the input data. Data is preprocessed to construct a training dataset which contains a matrix of technical patterns including EMA, Emerging Markets Small Cap (EMSD), relative strength index (RSI), etc. The dataset is put in numerical experiments contained different research aspects including base case ANN research, effects of different layers, effects of different activation functions, different outputs, different inputs and effects of additional technical indicators. The results have shown that the use of various technical indicators possibly prevents over-fitting in the classification of non-stationary financial time-series data, which enhances trading performance compared to primitive technical trading strategy. (Buy-and-Hold is the benchmark strategy in this experiment.)

Some classification and regression machine learning models are applied in cryptocurrency trading by predicting prices trends. More researchers focused on comparison of different classification and regression machine learning methods. Sun et al. [202] used random forests (RFs) with factors in Alpha01 [124] (capturing features from history of cryptocurrency market) to build a prediction model. The experiment collected data from API in cryptocurrency exchanges and selected 5-minute frequency data for backtesting. The results showed that the performances are proportional to the amount of data (more data, more accurate) and the factors used in the RF model appear to have different importance. For example, "Alpha024" and "Alpha032" features appeared as the most important in the model adopted. (The alpha features come from paper "101 Formulaic Alphas" [124].) Vo et al. [215] applied RFs in High-Frequency cryptocurrency Trading (HFT) and compared it with deep learning models. Minute-level data is collected when utilising a forward fill imputation methods to replace the NULL value (i.e., a missing value). Different periods and RF trees are tested in the experiments. The authors also compared F-1 precision and recall metrics between RF and Deep Learning (DL). The results showed that RF is effective despite multicollinearity occurring in ML features, the lack of model identification also potentially leading to overfitting; this research also attempted to create an HFT strategy for Bitcoin using RF. Maryna et al. [232] investigated the profitability of an algorithmic trading strategy based on training a SVM model to identify cryptocurrencies with high or low predicted returns. The results showed that the performance of the SVM strategy was the fourth being better only than S&P B&H strategy, which simply buys-and-hold the S&P index. (There are other 4 benchmark strategies in this research.)The authors observed that SVM needs a large number of parameters and so is very prone to overfitting, which caused its bad performance. Barnwal et al. [14] used generative and discriminative classifiers to create the stack model, particularly 3 generative and 6 discriminative classifiers and optimised over one-layer Neural Network, to predict the direction of cryptocurrency price. A discriminative classifier models the relationship between unknown and known data, and a generative classifier predicts unknown data by generating data and estimating assumptions and distributions of the model [172]. Technical indicators including trend, momentum, volume and volatility, are collected as features of the model. The authors discussed how different classifiers and features affect the prediction. Attanasio et al. [7] compared a variety of classification algorithms including SVM, NB and RF in predicting next-day price trends of a given cryptocurrency. The results showed that due to the heterogeneity and volatility of cryptocurrencies financial instruments, forecasting models based on a series of forecasts appeared better than classification technology in trading cryptocurrency. Madan et al. [156] modelled Bitcoin price prediction problem as a binomial classification task, experimenting with a custom algorithm that leverages both random forests and generalized linear models. Daily data, 10-minute data and 10-second data are used in the experiments. The experiments showed that 10-minute data gave a better sensitivity and specificity ratio than 10-second data (10-second prediction achieved around 10% accuracy). Considering predictive trading, 10-minute data helped show clearer trends in the experiment compared to 10-second backtesting. Similarly, Virk [214] compared RF, SVM, GB and LR to predict price of Bitcoin. The results showed that SVM achieved the highest accuracy of 62.31% and precision value 0.77 among binomial classification machine learning algorithms.

Different deep learning models are used in finding patterns of price trends in cryptocurrency market. Zhengy et al. [230] implemented two machine learning models, fully-connected ANN and LSTM to predict cryptocurrency price dynamics. The results showed that ANN in general outperforms LSTM although theoretically LSTM is more suitable than ANN in terms of modeling time series dynamics; the performance measures considered are MAE and RMSE in joint prediction (five cryptocurrencies daily prices prediction). The findings show that future state of a time series for cryptocurrencies is highly dependent on its historic evolution. Kwon et al. [144] used an LSTM model, with a three-dimensional price tensor representing the past price changes of cryptocurrencies as input. This model outperforms the GB model in terms of F1-score. Specifically, it has a performance improvement of about 7% over the GB model in 10-minute prices prediction. In particular, the experiments showed that LSTM is more suitable when classifying cryptocurrency data with high volatility. Alessandretti et al. [4] tested Gradient boosting decision trees (including single regression and XGBoost-augmented regression) and LSTM model on forecasting daily cryptocurrency prices. They found methods based on gradient boosting decision trees worked best when predictions were based on short-term windows of 5/10 days while LSTM worked best when predictions were based on 50 days of data. The relative importance of the features in both models are compared and an optimised portfolio composition (based on geometric mean return and Sharpe ratio) is discussed in this paper. Phaladisailoed et al. [180] chose regression models (Theil-Sen Regression and Huber Regression) and deep learning based models (LSTM and GRU) to compare the performance of predicting the rise and fall of Bitcoin price. In terms of two common measure metrics, MSE and R-Square (R^2), GRU shows the best accuracy. Fan et al. [88] applied an autoencoder-augmented LSTM structure in predicting mid-price of 8 cryptocurrency pairs. Level-2 limit order book live data is collected and the experiment achieved 78% accuracy of price movements prediction in high frequency trading (tick level). This research improved and verified the view of Sirignano et al. [197] that universal models have better performance than currency-pair specific models for cryptocurrency markets. Moreover, "Walkthrough" (i.e., retrain the original deep learning model itself when it appears to no longer be valid) is proposed as a method to optimise the training of a deep learning model and shown to significantly improve the prediction accuracy.

Researchers also focused on comparison or merge of statistical models and machine/deep learning models. Rane et al. [187] described classical time series prediction methods and machine learning algorithms used for predicting Bitcoin price. Statistical models such as Autoregressive Integrated Moving Average models (ARIMA), Binomial Generalized Linear Model and GARCH are compared with machine learning models such as SVM, LSTM and Non-linear Auto-Regressive with Exogenous Input Model (NARX). The observation and results showed that NARX model is the best model with nearly 52% predicting accuracy based on 10 seconds interval. Rebane et al. [188] compared traditional models like ARIMA with modern popular model like seq2seq in predicting cryptocurrency returns. The result showed that the seq2seq model exhibited demonstrable improvement over the ARIMA model for Bitcoin-USD prediction but showed very poor performance in extreme cases. The authors proposed performing additional investigations, such as the use of LSTM instead of GRU units to improve the performance. Similar models were also compared by Stuerner et al. [201] who explored the superiority of automated investment approach in trend following and technical analysis in cryptocurrency trading. Samuel et al. [179] explored vector auto-regressive model (VAR model), a more complex RNN, and a hybrid of the two in residual recurrent neural networks (R2N2) in predicting cryptocurrency returns. The RNN with ten hidden layers is optimised for the setting and the neural network augmented by VAR allows the network to be shallower, quicker and to have a better prediction than a RNN. RNN, VAR and R2N2 models are compared. The results showed that the VAR model has phenomenal test period performance and thus props up the R2N2 model, while the RNN performs poorly. This research is an attempt on optimisation of model design and applying to prediction on cryptocurrency returns.

7.2.3. Sentiment Analysis

Sentiment analysis, a popular research topic in the age of social media, has also been adopted to improve predictions for cryptocurrency trading.

Lamon et al. [146] used daily news and social media data labelled on actual price changes, rather than on positive and negative sentiment. By this approach, the prediction on price is replaced with positive and negative sentiment. The experiment acquired cryptocurrency related news article headlines from website like “cryptocoinsnews” and twitter API. Weights are taken in positive and negative words in cryptocurrency market. Authors compared LR, Linear Support Vector Machine (LSVM) and NB as classifiers and concluded that LR is the best classifier in daily price prediction with 43.9% of price increases correctly predicted and 61.9% of price decreases correctly forecasted. Smuts [198] conducted similar binary sentiment-based price prediction method with a LSTM model using Google Trends and Telegram sentiment. In detail, the sentiment was extracted from Telegram by using a novel measure called VADER [117]. The backtesting reached 76% accuracy on the test set during the first half of 2018 in predicting hourly prices. Nasir et al. [170] researched relationship between cryptocurrency returns and search engines. The experiment employed a rich set of established empirical approaches including VAR framework, copulas approach and non-parametric drawings of time series. The results found that Google searches exert significant influence on Bitcoin returns, especially in short-term interval. Kristoufek [141] discussed positive and negative feedback of Google trends or daily views on Wikipedia. The author mentioned different methods including Cointegration, Vector autoregression and Vector error-correction model to find causal relationships between prices and searched terms in cryptocurrency market. The results indicated that the search trends and cryptocurrency prices are connected. There is also a clear asymmetry between the effects of increased interest in currencies above or below their trend values from the experiment. Young et al. [138] analysed user comments and replies in online communities and its connection with cryptocurrency volatility. After crawling comments and replies in online communities, authors tagged the extent of positive and negative topics. Then relationship between price and number of transaction of cryptocurrency is tested according to comments and replies to selected data. At last, a prediction model using machine learning based on selected data is created to predict fluctuations in cryptocurrency market. The results show the amount of accumulated data and animated community activities exerted a direct effect on fluctuation in the price and volume of cryptocurrency.

Phillips et al. [185] applied dynamic topic modelling and Hawkes model to decipher relationships between topics and cryptocurrency price movements. Authors used Latent Dirichlet allocation (LDA) model for topic modelling, which assumes each document contains multiple topics to different extents. The experiment showed that particular topics tend to precede certain types of price movements in cryptocurrency market and authors proposed the relationships could be built into a real-time cryptocurrency trading. Li et al. [150] analysed Twitter sentiment and trading volume and an Extreme Gradient Boosting Regression Tree Model in prediction of ZClassic (ZCL) cryptocurrency market. Sentiment analysis using natural language processing from Python package “Textblob” assigns impactful words a polarity value. Values of weighted and unweighted sentiment indices are calculated on hourly basis by suming weights of coinciding tweets, which makes us compare this index to ZCL price data. The model achieved a Pearson correlation of 0.806 when applied to test data, yielding a statistical significance at the $p<0.0001$ level. Flori [92] relied on a Bayesian framework that combines market-neutral information with subjective beliefs to construct diversified investment strategies in Bitcoin market. The result shows that news and media attention seem to contribute to influence the demand for Bitcoin and enlarge the perimeter of the potential investors, probably stimulating price euphoria and upwards-downwards market dynamics. Author’s research highlighted the importance of news in guiding portfolio rebalancing.

Similarly, Colianni et al. [69], Garcia et al. [98], Zamuda et al. [226] et al. used sentiment analysis technology applying in cryptocurrency trading area and had similar results. Colianni et al. [69] cleaned data and apply supervised machine learning algorithms such as logistic regression, Naive Bayes and support vector machines, etc. in Twitter Sentiment Analysis in cryptocurrency trading. The experiment results in this paper lead to a final hour-to-hour and day-to-day prediction accuracy exceeding 90%. Garcia et al. [98] applied multidimensional analysis and impulse analysis in social signals of sentiment effects and algorithmic trading of Bitcoin. The results verified the long-standing assumption that transaction-based social media sentiment has the potential to generate a positive return on investment. Zamuda et al. [226] adopted new sentiment analysis indicators and used multi-target portfolio selection to avoid risks in cryptocurrency trading. The perspective is rationalized based on the elastic demand for computing resources of the cloud infrastructure. An general model evaluating influence between user’s network Action-Reaction-Influence-Model (ARIM) is mentioned in this research. Bartolucci et al. [15] researched cryptocurrency prices with the “Butterfly effect”, which means “issues” of open-source project provides insights to improve prediction of cryptocurrency prices. Sentiment, politeness, emotions analysis of GitHub comments are applied in Ethereum and Bitcoin markets. The results showed that effect metrics time series have predictive power over cryptocurrency prices.

7.2.4. Reinforcement Learning

The deep reinforcement algorithm bypasses prediction and goes straight to market management actions to achieve higher profit [111]. Bu et al. [40] proposed a combination of double Q-network and unsupervised pre-training using DBM to generate and enhance the optimal Q-function in cryptocurrency trading. The trading model contains agents in series in the form of two neural networks, unsupervised learning modules and environments. The input market state connects a encoding network which includes spectral feature extraction (convolution-pooling module) and temporal feature extraction (LSTM module). A double-Q network follows encoding network and actions are generated from this network. Compared to existing deep learning models (LSTM, CNN, MLP, etc.), this model achieved highest profit even facing an extreme market situation (recorded 24% of profit while cryptocurrency market price drops by -64%). Juchli [122] applied two implementations of reinforcement learning agents, a Q-Learning agent, which serves as the learner when no market variables are provided, and a DQN agent which was developed to handle the features previously mentioned. The DQN agent was backtested under the application of two different neural network architectures. The results showed that the DQN-CNN agent (convolutional neural network) is superior to the DQN-MLP agent (multilayer perceptron) in backtesting prediction. Lucarelli et al. [154] focused on improving automated cryptocurrency trading with a deep reinforcement learning approach. Double and Dueling double deep Q-learning networks are compared for 4 years. By setting rewards functions as Sharpe ratio and profit, the double Q-learning method is demonstrated to be the most profitable approach in trading cryptocurrency.

7.3. Others

Atsalakis et al. [6] proposes a computational intelligence technique that uses a hybrid Neuro-Fuzzy controller, namely PATSOS, to forecast the direction in the change of the daily price of Bitcoin. The proposed methodology outperforms two other computational intelligence models, the first being developed with a simpler neuro-fuzzy approach, and the second being developed with artificial neural networks. According to the signals of the proposed model, the investment return obtained through trading simulation is 71.21% higher than the investment return obtained through a simple buy and hold strategy. This application is proposed for the first time in forecasting of Bitcoin price movements. Topological data analysis is applied to forecasting price trends of cryptocurrency markets in [137]. The approach is to harness topological features of attractors of dynamical systems for arbitrary temporal data. The results showed that the method can effectively access important topological patterns and sampling noise (like bid–ask bounces, discreteness of price changes, differences in trade sizes or informational content of price changes etc.) by providing theoretical results. Kurbucz [142] designed a complex method consisting of single-hidden layer feedforward neural networks (SLFNs) to (i) determine the predictive power of the most frequent edges of the transaction network (a public ledger that records all Bitcoin transactions) on the future price of Bitcoin; and, (ii) to provide an efficient technique for applying this untapped dataset in day trading. The research found a significantly high accuracy (60.05%) for the price movement classifications and this information can be obtained using a small subset of edges (approximately 0.45% of all unique edges).

8. Portfolio and Cryptocurrency Assets

8.1. Research among cryptocurrency pairs and related factors

Ji et al. [119] examined connectedness via return and volatility spillovers across six large cryptocurrencies (collected from coinmarketcap lists from August 7 2015 to February 22 2018) and found Litecoin and Bitcoin to have the most effect on other cryptocurrencies. The authors followed methods of Diebold et al. [77] and built positive/negative returns and volatility connectedness networks. Furthermore, the regression model is used to identify drivers of various cryptocurrency integration levels. Further analysis revealed that the relationship between each cryptocurrency in terms of return and volatility is not necessarily due to its market size. Adjepong et al. [175] explored market coherence and volatility causal linkages of seven leading cryptocurrencies. Wavelet-based methods are used to examine market connectedness. Parametric and nonparametric tests are employed to investigate directions of volatility spillovers of the assets. Experiments revealed from diversification benefits to linkages of connectedness and volatility in cryptocurrency markets.

Some researchers explored relationship between cryptocurrency and different factors, including futures, gold etc. Hale et al. [108] suggested that Bitcoin prices rise and fall rapidly after CME issues futures consistent with pricing dynamics. Specifically, the authors pointed out that the rapid rise and subsequent decline in prices after the introduction of futures is consistent with trading behaviour in cryptocurrency market. Bai et al. [11] studied a trading algorithm for foreign exchange on a cryptocurrency Market using Automated Triangular Arbitrage method. Implementing pricing strategy, implementing trading algorithms and developing a given trading simulation are three problems solved by this research. Kang et al. [129] examined the hedging and diversification properties of gold futures versus Bitcoin prices by using dynamic conditional correlations (DCCs) and wavelet coherence. DCC-GARCH model [83] is used to estimate the time-varying correlation between Bitcoin and gold futures by modelling the variance and the co-variance but also this two flexibility. Wavelet coherence method focused more on co-movement between Bitcoin and gold futures. From experiments, the wavelet coherence results indicated volatility persistence, causality and phase difference between Bitcoin and gold. Dyhrberg et al [80] applied GARCH model and the exponential GARCH model in analysing similarities between Bitcoin, gold and the US dollar. The experiments showed that Bitcoin, gold and the US dollar have similarity with the variables of the GARCH model, have similar hedging capabilities and react symmetrically to good and bad news. The authors observed that Bitcoin can combine some advantages of commodities and currencies in financial markets to be a tool for portfolio management. Baur et al. [16] extended the research of Dyhrberg et al.; same data and sample periods are tested [80] with GARCH and EGARCH-(1,1) models but the experiments reached different conclusions. Baur et al. found that Bitcoin has unique risk-return characteristics compared with other assets. They noticed that Bitcoin excess returns and volatility resemble a rather highly speculative asset with respect to gold or the US dollar. Bouri et al. [34] studied relationship between Bitcoin and energy commodities by applying DCCs and GARCH (1,1) model. In particular, the results showed that Bitcoin is a strong hedge and safe haven for energy commodities. Kakushadze [125] proposed factor models for the cross-section of daily cryptoasset returns and provided source code for data downloads, computing risk factors and backtesting for all cryptocurrencies and a host of various other digital assets. The results showed that cross-sectional statistical arbitrage trading may be possible for cryptoassets subject to efficient executions and shorting. Beneki et al. [21] tested hedging abilities between Bitcoin and Ethereum by a multivariate BEKK-GARCH methodology and impulse response analysis within VAR model. The results indicated a volatility transaction from Ethereum to Bitcoin, which implied possible profitable trading strategies on the cryptocurrency derivative market. Guglielmo et al. [45] examined week effect in cryptocurrency markets and explored the feasibility of this indicator in trading practice. Student t-test, ANOVA, Kruskal–Wallis and Mann–Whitney tests were carried out for cryptocurrency data in order to compare time periods that may be characterized by anomalies with other time periods. When anomaly is detected, an algorithm was established to exploit profit opportunities (MetaTrader terminal in MQL4 is mentioned in this research). The results showed evidence of anomaly (abnormal positive returns on Mondays) in Bitcoin market by backtesting in 2013-2016.

8.2. Crypto-asset Portfolio Research

Some researchers applied portfolio theory for crypto assets. Corbet et al. [72] gave a systematic analysis of cryptocurrencies as financial assets. Brauneis et al. [37] applied the Markowitz mean-variance framework in order to assess risk-return benefits of cryptocurrency portfolios. In an out-of-sample analysis accounting for transaction cost, they found that combining cryptocurrencies enriches the set of ‘low’-risk cryptocurrency investment opportunities. In terms of the Sharpe ratio and certainty equivalent returns, the $1/N$-portfolio (i.e., “naive” strategies, such as equally dividing amongst asset classes) outperformed single cryptocurrencies and more than 75% in terms of the Sharpe ratio and certainty equivalent returns of mean-variance optimal portfolios. Castro et al. [47] developed a portfolio optimisation model based on the Omega measure which is more comprehensive than the Markowitz model, and applied this to four crypto-asset investment portfolios by means of a numerical application. Experiments showed crypto-assets improves the return of the portfolios, but on the other hand, also increase the risk exposure.

Bedi et al. [18] examined diversification capabilities of Bitcoin for a global portfolio spread across six asset classes from the standpoint of investors dealing in five major fiat currencies, namely US Dollar, Great Britain Pound, Euro, Japanese Yen and Chinese Yuan. They employed modified Conditional Value-at-Risk and standard deviation as measures of risk to perform portfolio optimisations across three asset allocation strategies and provided insights into sharp disparity in Bitcoin trading volumes across national currencies from a portfolio theory perspective. Similar research has been done by Antipova et al. [5], which explored the possibility of establishing and optimizing a global portfolio by diversifying investments using one or more cryptocurrencies, and assessing returns to investors in terms of risks and returns. Fantazzini et al. [89] proposed a set of models which can be used to estimate the market risk for a portfolio of crypto-currencies, and simultaneously estimate their credit risk using the Zero Price Probability (ZPP) model. The results revealed the superiority of the t-copula/skewed-t GARCH model for market risk, and the ZPP-based models for credit risk.

Trucios et al. [212] proposed a methodology based on vine copulas and robust volatility models to estimate the Value-at-Risk (VaR) and Expected Shortfall (ES) of cryptocurrency portfolios. The proposed algorithm displayed good performance in estimating both VaR and ES. Hrytsiuk et al. [114] showed that the cryptocurrency returns can be described by the Cauchy distribution and obtained the analytical expressions for VaR risk measures and performed calculations accordingly. As a result of the optimisation, the sets of optimal cryptocurrency portfolios were built in their experiments.

Jiang et al. [120] proposed a two-hidden-layer CNN that takes the historical price of a group of cryptocurrency assets as an input and outputs the weight of the group of cryptocurrency assets. Training is conducted in an intensive manner to maximise cumulative returns, which is considered a reward function of the CNN network. The performance of the CNN strategy is compared with the three benchmarks and the other three portfolio management algorithms (buy and hold strategy, Uniform Constant Rebalanced Portfolio and Universal Portfolio with Online Newton Step and Passive Aggressive Mean Reversion); the results are positive in that the model is only second to the Passive Aggressive Mean Reversion algorithm (PAMR). Estalayo et al. [87] reported initial findings around the combination of DL models and Multi-Objective Evolutionary Algorithms (MOEAs) for allocating cryptocurrency portfolios. Technical rationale and details were given on the design of a stacked DL recurrent neural network, and how its predictive power can be exploited for yielding accurate ex ante estimates of the return and risk of the portfolio. Results obtained for a set of experiments carried out with real cryptocurrency data have verified the superior performance of their designed deep learning model with respect to other regression techniques.

9. Market Condition Research

9.1. Bubbles and Crash Analysis

Phillips and Yu proposed a methodology to test for the presence of cryptocurrency bubble [58], which is extended by Shaen et al. [73]. The method is based on supremum Augmented Dickey–Fuller (SADF) to test for the bubble through the inclusion of a sequence of forward recursive right-tailed ADF unit root tests. An extended methodology generalised SADF (GSAFD), is also tested for bubbles within cryptocurrency data. The research concluded that there is no clear evidence of a persistent bubble in cryptocurrency markets including Bitcoin or Ethereum. Bouri et al. [36] date-stamped price explosiveness in seven large cryptocurrencies and revealed evidence of multiple periods of explosivity in all cases. GSADF is used to identify multiple explosiveness periods and logistic regression is employed to uncover evidence of co-explosivity across cryptocurrencies. The results showed that the likelihood of explosive periods in one cryptocurrency generally depends on the presence of explosivity in other cryptocurrencies and points toward a contemporaneous co-explosivity that does not necessarily depend on the size of each cryptocurrency.

Extended research by Phillips et al. [181, 182] (who applied a recursive augmented Dickey-Fuller algorithm, which is called PSY test) and Landsnes et al. [85] studied possible predictors of bubble periods of certain cryptocurrencies. The evaluation includes multiple bubble periods in all cryptocurrencies. The result shows that higher volatility and trading volume is positively associated with the presence of bubbles across cryptocurrencies. In terms of bubble prediction, authors found the probit model to perform better than the linear models.

Phillips et al. [183] used Hidden Markov Model (HMM) and Superiority and Inferiority Ranking (SIR) method to identify bubble-like behaviour in cryptocurrency time series. Considering HMM and SIR method, epidemic detection mechanism is used in social media to predict cryptocurrency price bubbles, which classify bubbles through epidemic and non-epidemic labels. Experiments have demonstrated a strong relationship between Reddit usage and cryptocurrency prices. This work also provides some empirical evidence that bubbles mirror the social epidemic-like spread of an investment idea. Guglielmo et al. [44] examined the price overreactions in the case of cryptocurrency trading. Some parametric and non-parametric tests confirmed presence of price patterns after overreactions, which identified that the next-day price changes in both directions are bigger than after "normal" days. The results also showed that the overreaction detected in the cryptocurrency market would not give available profit opportunities (possibly due to transaction costs) that cannot be considered as evidence of the EMH. Chaim et al. [53] analysed high unconditional volatility of cryptocurrency from a standard log-normal stochastic volatility model to discontinuous jumps of volatility and returns. The experiment indicated the importance of incorporating permanent jumps to volatility in cryptocurrency markets.

9.2. Extreme condition

Differently from traditional fiat currencies, cryptocurrencies are risky and exhibit heavier tail behaviour. Paraskevi et al. [134] found extreme dependence between returns and trading volumes. Evidence of asymmetric return-volume relationship in the cryptocurrency market was also found by experiment, as a result of discrepancies in the correlation between positive and negative return exceedances across all the cryptocurrencies.

There has been a price crash in late 2017 to early 2018 in cryptocurrency [225]. Yaya et al. [225] researched persistence and dependence of Bitcoin on other popular alternative coins before and after 2017/18 crash in cryptocurrency markets. The result showed that higher persistence of shocks is expected after the crash due to speculations in the mind of cryptocurrency traders, and more evidences of non-mean reversions, implying chances of further price fall in cryptocurrencies.

10. Others related to Cryptocurrency Trading

Some other research papers related to cryptocurrency trading treat distributed in market behaviour, regulatory mechanisms and benchmarks.

Krafft et al. [140] and Yang [224] analysed market dynamics and behavioural anomalies respectively to understand effects of market behaviour in cryptocurrency market. Krafft et al. discussed potential ultimate causes, potential behavioural mechanisms and potential moderating contextual factors to enumerate possible influence of GUI and API on cryptocurrency markets. Then they highlighted potential social and economic impact of human-computer interaction in digital agency design. Yang applied behavioural theories of asset pricing anomalies in testing 20 market anomalies using cryptocurrency trading data. The results showed that anomaly research focused more on the role of speculators, which gave a new idea to research the momentum and reversal in cryptocurrency market.

Leclair [148] and Vidal-Thomás et al. [213] analysed the existence of herding in the cryptocurrency market. Leclair applied herding methods of Huang and Salmon [118] in estimating the market herd dynamics in the CAPM framework. Vidal-Thomás et al. analyse the existence of herds in the cryptocurrency market by returning cross-sectional standard (absolute) deviations. Both their findings showed significant evidence of market herding in cryptocurrency market. Makarov et al. [157] studied price impact and arbitrage dynamics in the cryptocurrency market and found that 85% of the variations in bitcoin returns and the idiosyncratic components of order flow play an important role in explaining the size of the arbitrage spreads between exchanges.

In November 2019, Griffin et al. put forward a paper on the thesis of unsupported digital money inflating cryptocurrency prices [104], which caused a great stir in the academic circle and public opinion. Using algorithms to analyse Blockchain data, they found that purchases with Tether are timed following market downturns and result in sizeable increases in Bitcoin prices. By mapping the blockchains of Bitcoin and Tether, they were able to establish that one large player on Bitfinex uses Tether to purchase large amounts of Bitcoin when prices are falling and following the prod of Tether.

More researches involved benchmark and development in cryptocurrency market [112, 231], regulatory framework analysis [193], data mining technology in cryptocurrency trading [177], application of efficient market hypothesis in cryptocurrency market [196] and artificial financial markets for studying a cryptocurrency market [64]. Hileman et al. [112] segmented the cryptocurrency industry into four key sectors: exchanges, wallets, payments and mining. They gave a benchmarking study of individuals, data, regulation, compliance practices, costs of firms and global map of mining in cryptocurrency market in 2017. Zhou et al. [231] discussed the status and future of computer trading in the largest group of Asia-Pacific economies and then considered algorithmic and high frequency trading in cryptocurrency markets as well. Shanaev et al. [193] used data on 120 regulatory events to study the implications of cryptocurrency regulation and the results showed that stricter regulation of cryptocurrency is not desirable. Akhilesh et al. [177] used the average absolute error calculated between the actual and predicted values of the market sentiment of different cryptocurrencies on that day as a method for quantifying the uncertainty. They used the comparison of uncertainty quantification methods and opinion mining to analyse current market conditions. Sigaki et al. [196] used permutation entropy and statistical complexity on the sliding time window returned by the price log to quantify the dynamic efficiency of more than four hundred cryptocurrencies. As a result, the cryptocurrency market showed significant compliance with efficient market assumptions. Cocco et al. [64] described an agent-based artificial cryptocurrency market in which heterogeneous agents buy or sell cryptocurrencies. The proposed simulator is able to reproduce some real statistical properties of price returns observed in the Bitcoin real market. Marko [174] considered the future use of cryptocurrencies as money based on the long-term value of cryptocurrencies. Neil et al. [97] analysed the influence of network effect on the competition of new cryptocurrency markets.

There also exists some research and papers introducing the basic process and rules of cryptocurrency trading including findings of Hansel et al. [109], Kate [131], Garza et al. [99], Ward et al. [220]. Hansel et al. [109] introduced basics of cryptocurrency, Bitcoin and Blockchain, ways to identify profitable trend in the market, ways to use Altcoin trading platforms such as GDAX and Coinbase, methods of using a crypto wallet to store and protect the coins in their book. Kate et al. [131] set six steps to show how to start an investment without any technical skills in cryptocurrency market. This book is an entry-level trading manual for starters learning cryptocurrency trading. Garza et al. [99] simulated automatic cryptocurrency trading system, which helps investors limit systemic risks and improve market returns. This paper is an example to start designing an automatic cryptocurrency trading system. Ward st al. [220] discussed algorithmic cryptocurrency trading using several general algorithms, and modifications thereof including adjusting the parameters used in each strategy, as well as mixing multiple strategies or dynamically changing between strategies. This paper is an example to start algorithmic trading in cryptocurrency market.

11. Summary Analysis of Literature Review

This section analyses the timeline, the research distribution among technology and methods, the research distribution among properties. It also summarises the datasets that have been used in cryptocurrency trading research.

11.1. Timeline

Figure 8 shows several major events in cryptocurrency trading. The timeline contains milestone events in cryptocurrency trading and important scientific breakthroughs in this area.

As early as 2009, Satoshi Nakamoto proposed and invented first decentralised cryptocurrency, Bitcoin [167]. It is considered to be the start of cryptocurrency. In 2010, the first cryptocurrency exchange was founded, which means cryptocurrency would not be an OTC market but traded on exchanges based on auction market system.

In 2013, Kristoufek [141] concluded that there is a strong correlation between Bitcoin price and the frequency of "Bitcoin" search queries in Google Trends and Wikipedia. In 2014, Lee and Yang [149] firstly proposed to check causality from copula-based causality in the quantile method from trading volumes of seven major cryptocurrencies to returns and volatility.

In 2015, Cheah et al. [56] discussed bubble and speculation of Bitcoin and cryptocurrencies. In 2016, Dyhrberg [80] explored Bitcoin volatility using GARCH models combined with gold and US dollars.

From late 2016 to 2017, machine learning and deep learning technology were applied in prediction of cryptocurrency return. In 2016, McNally et al. [160] predicted Bitcoin price using LSTM algorithm. Bell and Zbikowski et al. [19, 227] applied SVM algorithm to predict trends of cryptocurrency price. In 2017, Jiang et al. [120] used double Q-network and pretrained it using DBM for the prediction of cryptocurrencies portfolio weights.

In recent years, several research directions including cross asset portfolios [18, 47, 37], transaction network applications [142, 36], machine learning optimisation [187, 6, 230] have been considered in the cryptocurrency trading area.

Figure 8: Timeline of cryptocurrency trading research

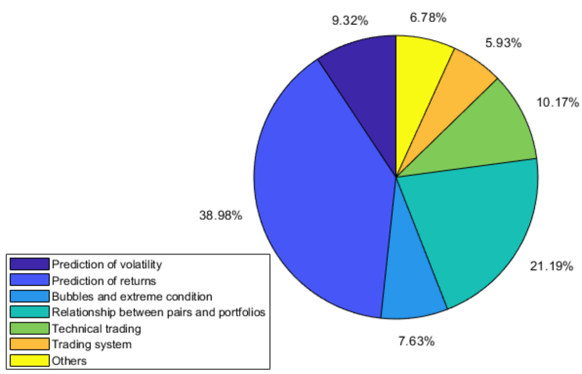

Figure 9: Research distribution among cryptocurrency trading properties

11.2. Research Distribution among Properties

We counted the number of papers covering different aspects of cryptocurrency trading. Figure 9 shows the result. The attributes in the legend are ranked according to the number of papers that specifically test the attribute.

Over one-third (38.98%) of the papers research prediction of returns. Another one-third of papers focuses on researching bubbles and extreme conditions and relationship between pairs and portfolios in cryptocurrency trading. The remaining researching topics (prediction of volatility, trading system, technical trading and others) have roughly one third share.

11.3. Research Distribution among Categories and Technologies

This section introduces and compares categories and technologies in cryptocurrency trading. When papers cover multiple technologies or compare different methods, we draw statistics from the different technical perspectives.

Among all the 118 papers, 79 papers (66.95%) cover statistical methods and machine learning categories. These papers basically research technical-level cryptocurrency trading including mathematical modelling and statistics. Other papers related to trading systems on pure technical indicators and introducing the industry and its history are not included in this analysis. Among all 79 papers, 60 papers (77.22%) present statistical methods and technologies in cryptocurrency trading research and 25.35% papers research machine learning applied to cryptocurrency trading (cf. Figure 10). It is interesting to mention that, there are 16 papers (25.32%) applying and comparing more than one technique in cryptocurrency trading. More specifically, Bach et al. [9], Alessandretti et al. [4], Vo et al. [215], Phaladisailoed et al. [180], Siaminos [195], Rane et al. [187] used both statistical methods and machine learning methods in cryptocurrency trading.

Table 7
Search hits of research distribution in all trading areas

Technology Category	Google Scholar hits	Google hits	Arxiv hits
Statistical methods	1.22M	62M	1240
Machine learning methods	483K	150M	520

Table 7 shows the results of search hits in all trading areas (not limited to cryptocurrencies) . From the table, we can see that most research findings focused on statistical methods in trading, which means most of the research on traditional markets still focused on using statistical methods for trading. But we observed that machine learning in trading had a higher degree of attention. It might because the traditional technical and fundamental have been arbitraged, so the market has moved in recent years to find new anomalies to exploit. Meanwhile, the results also showed there exist many opportunities for research in the widely studied areas of machine learning applied to trading in cryptocurrency markets (cf. Section 12).

11.3.1. Research Distribution among Statistical methods

As from Figure 10, we further classified the papers using statistical methods into 6 categories: (i) basic regression methods; (ii) linear classifiers and clustering; (iii) time-series analysis; (iv) decision trees and probabilistic classifiers; (v) modern portfolios theory; and, (vi) Others.

Basic regression methods include regression methods (Linear Regression), function estimation and CGCD method. **Linear Classifiers and Clustering** include SVM and KNN algorithm. **Time-series analysis** include GARCH model, BEKK model, ARIMA model, Wavelet time-scale method. **Decision Trees and probabilistic classifiers** include Boosting Tree, RF model. **Modern portfolio theory** include Value-at-Risk (VaR) theory, expected-shortfall (ES), Markowitz mean-variance framework. **Others** include industry, market data and research analysis in cryptocurrency market.

The figure shows that basic Regression methods and time-series analysis are the most commonly used methods in this area.

11.3.2. Research Distribution among Machine Learning Categories

Papers using machine learning account for 22.78% (c.f Figure 10) of the total. We further classified these papers into three categories: (vii) ANNs, (viii) LSTM/RNN/GRUs, and (ix) DL/RL.

The figure also shows that methods based on LSTM, RNN and GRU are the most popular in this subfield.

ANNs contain papers researching ANN applications in cryptocurrency trading such as back propagation (BP) NN. **LSTM/RNN/GRUs** include papers using neural networks which exploit the temporal structure of the data, a technology especially suitable for time series prediction and finan-

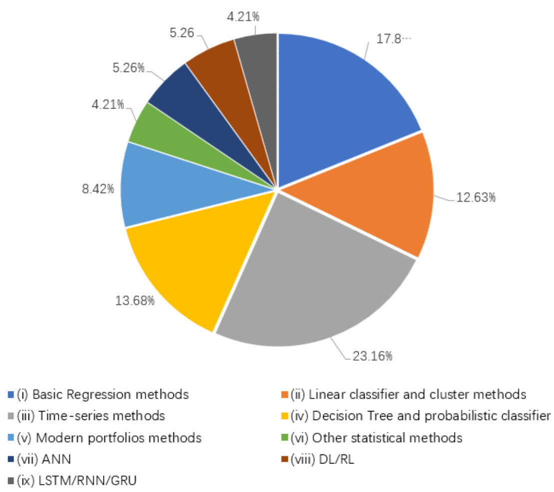

Figure 10: Research distribution among cryptocurrency trading technologies and methods

cial trading. **DL/RL** include papers using Multilayer Neural Networks and Reinforcement Learning. The difference between ANN and DL is that generally DL refers to an ANN with multiple hidden layers while ANN refers to simple structure neural network contained input layer, hidden layer (one or multiple), and an output layer.

11.4. Datasets used in Cryptocurrency Trading

Tables 8–10 show the details for some representative datasets used in cryptocurrency trading research. Table 8 shows the market datasets. They mostly include price, trading volume, order-level information, collected from cryptocurrency exchanges. Table 9 shows the sentiment-based data. Most of datasets in this table contain market data and media/Internet data with emotional or statistical labels. Table 10 gives two examples of datasets used in the collected papers that are not covered in the first two tables.

The column "Currency" shows the types of cryptocurrencies included; this shows that Bitcoin is the most commonly used currency for cryptocurrency researches. The column "Description" shows general description and types of datasets. The column "Data Resolution" means latency of the data (e.g., used in the backtest) – this is useful to distinguish between high frequency trading and low frequency trading. The column "Time range" shows the time span of datasets used in experiments; this is convenient to distinguish between the current performance in a specific time interval and the long-term effect. We also present how the dataset has been used (i.e., the task), cf. column "Usage". "Data Sources" gives details on where the data is retrieved from, including cryptocurrency exchanges, aggregated cryptocurrency index and user forums (for sentiment analysis).

12. Opportunities in Cryptocurrency Trading

This section discusses potential opportunities for future research in cryptocurrency trading.

Sentiment-based research. As discussed above, there is a substantial body of work, which uses natural language processing technology, for sentiment analysis with the ultimate goal of using news and media contents to improve the performance of cryptocurrency trading strategies.

Possible research directions may lie in larger volume of media input (e.g., adding video sources) in sentiment analysis; updating baseline natural language processing model to perform more robust text preprocessing; applying neural networks in label training; extending samples in terms of holding period; transaction-fees; and, user reputation research.

Long-and-short term research. There are significant differences between long and short time horizons in cryptocurrency trading. In long-term trading, investors might obtain greater profits but have more possibilities to control risk when managing a position for weeks or months. On the other hand, the longer the horizon, the higher the risk and the most important the risk control. The shorter the horizon, the higher the cost and the lower the risk, so cost takes over the design of a strategy. In short-term trading, automated algorithmic trading can be applied when holding periods are less than a week. Researchers can differentiate between long-term and short-term trading in cryptocurrency trading by applying wavelet technology analysing bubble regimes [184] and considering price explosiveness [36] hypotheses for short-term and long-term research.

The existing work is mainly about showing the differences between long and short-term in trading cryptocurrency. Long-term in trading means less time would be cost in trend tracing and simple technical indicators in market analysis. Short-term in trading can limit overall risk because small positions are used in every transactions. But market noise (interference) and short transaction time might cause some stress in short term trading. It might also be interesting to explore extraction of trading signals, time series research, application to portfolio management, relationship between huge market crash and small price drop, derivative pricing in cryptocurrency market etc.

Correlation between cryptocurrency and others. By the effects of monetary policy and business cycles that are not controlled by the central bank, cryptocurrency is always negatively correlated with overall financial market trends. There have been some studies discussing correlations between cryptocurrencies and other financial markets [129, 47], which can be used to predict the direction of the cryptocurrency market.

Considering the characteristics of cryptocurrency, correlation between cryptocurrency and other assets still requires further research. Possible breakthroughs might be achieved with principal component analysis, relationship between cryptocurrency and other currencies in extreme conditions (i.e., financial collapse).

Bubbles and crash research. To discuss the high volatility and return of cryptocurrencies, current research has focussed on bubbles of cryptocurrency markets [58], correlation between cryptocurrency bubbles and indicators like

Table 8
Datasets (1/3):Market Data

Research Source	Description	Currency	Data Resolution	Time Range	Usage	Data Sources
Bouri et al. [35]	price, volatility, detrended volume data	Bitcoin, Ethereum, 5 other cryptocurrencies	daily	From: 2013/01/01 To: 2017/12/31	Prediction of volatility/return	CoinMarketCap
Nakano et al. [168]	high frequency price, volume data	Bitcoin	15min	From: 2016/07/31 To: 2018/01/24	Prediction of return	Poloniex
Bu et al. [40]	three pieces time slice for different research objectives	Bitcoin and seven altcoins	Not mentioned	From: 2016/05/14 To: 2016/07/03 From: 2018/01/01 To: 2018/01/31 From: 2017/07/01 To: 2017/07/31	Maximum profit with DRL	Not mentioned
Sun et al. [202]	price, volatility	ETC-USDT, other 12 cryptocurrencies	1 minute, 5 minutes, 30 minutes, one hour, one day	From: August 2017 To: December 2018	Prediction of return	Binance, Bitfinex
Guo et al. [106]	volatility, order book data	Bitcoin	hourly volatility observations, order book snapshots	From: September 2015 To: April 2017	Prediction of volatility	Not mentioned
Vo et al. [215]	timestamps, the OHLC prices etc.	Bitcoin	1minute	From: Starting 2015 To: End 2016	Prediction of return	Bitstamp, Btce, Btcn, Coinbase, Coincheck, and Kraken
Ross et al. [183]	price	Bitcoin, other 3 cryptocurrencies	daily	From: April 2015 To: September 2016	Predicting bubbles	CryptoCompare
Yaya et al. [225]	price	Bitcoin, other 12 cryptocurrencies	daily	From: 2015/08/07 To: 2018/11/28	Bubbles and crashes	Coin Metrics
Brauneis et al. [37]	individual price, trading volume	500 most capitalized Cryptocurrencies	daily	From: 2015/01/01 To: 2017/12/31	Portfolios management	CoinMarketCap
Feng et al. [90]	order-level USD/BTC trading data	Bitcoin	order-level	From: 2011/09/13 To: 2017/07/17	Trading strategy	Bitstamp

Table 9
Datasets (2/3):Sentiment-based data

Research Source	Description	Currency	Time range	Usage	Data Sources
Kim et al. [138]	Online cryptocurrency communities data and market data	Bitcoin,Ethereum, Ripple	From: December 2013 To: August, 2016 (Bitcoin) From: August 2015 To: August, 2016 (Ethereum) From: Creation To: August, 2016 (Ripple)	Prediction of fluctuation	Each community's HTML page
Phillips et al. [185]	Social media data and orice data	Bitcoin and Ethereum	From: 2016/08/30 To: 2017/08/30	Predict Mutual-Excitation of Cryptocurrency Market Returns	Reddit
Smtus [198]	Hourly data on price and trading volume and search terms from Google Trends	Bitcoin, Ethereum and their respective pricedrivers	From: 2017/12/01 To: 2018/06/30	Prediction of price	Google Trends, Telegram chat groups
Lamon et al. [146]	Daily price data and cryptocurrency related news article headlines	Bitcoin, Ethereum, Litecoin	From: 2017/01/01 To: 2017/11/30	Prediction of price	Kaggle, news headline
Phillips et al. [184]	Price and social media factors from Reddit	Bitcoin, Ethereum, Monero	From: 2010/09/10 To: 2017/05/31 (Bitcoin) Others can reference the paper	Waveletcoherence analysis of price	BraveNewCoin
Kang et al. [128]	Market data and posts and comments including metadata	Bitcoin	From: 2009/11/22 To: 2018/02/02	Relationships Between Bitcoin Prices and User Groups in Online Community	Bitcoin forum

volatility index (VIX) [85] (which is a "panic index" to measure the implied volatility of S&P500 Index Options), spillover effects in cryptocurrency market [155].

Additional research for bubbles and crashes in cryptocurrency trading could include a connection between the process of bubble generation and financial collapse and conducting a coherent analysis (coherent process analysis from the formation of bubbles to aftermath analysis of bubble

Table 10
Datasets (3/3):Others

Research Source	Description	Time range	Usage	Data Sources
Kurbucz [142, 139]	Raw and preprocessed data of all Bitcoin transactions and daily returns	From: 2016/11/09 To: 2018/02/05	Predicting the price of Bitcoin with transaction network	Bitcoin network dataset [164]
Bedi et al. [18]	A diversified portfolio including equity, fixedincome, real estate, alternative investments, commodities and money market	From: July 2010 To: December 2018	Cross-currency including cryptocurrency researching portfolios	Portfolio sources [18]

burst), analysis of bubble theory by Microeconomics, trying other physical or industrial models in analysing bubbles in cryptocurrency market (i.e., *Omori law* [221]), discussing the supply and demand relationship of cryptocurrency in bubble analysis (like using supply and demand graph to simulate the generation of bubbles and simulate the bubble burst).

Game theory and agent-based analysis. Applying game theory or agent-based modelling in trading is a hot research direction in traditional financial market. It might also be interesting to apply this method to trading in cryptocurrency markets.

13. Conclusions

We provided a comprehensive overview and analysis of research work of cryptocurrency trading. This survey presented the definitions and current state of the art. We also summarised the datasets used for experiments, and analysed the research trends and opportunities in cryptocurrency trading. We expect this survey to be beneficial to academics (e.g., finance researchers) and quantitative traders alike. The survey represents a quick way to get familiar with the literature on cryptocurrency trading, and can motivate more researchers to contribute to the pressing problems in the area, for example along the lines we have identified.

References

[1] 3commas, 2020. 3commas smart trading terminal and auto trading bots. https://3commas.io/. [Online, Accessed: January 26, 2020].

[2] Adeyanju, C., 2019. What crypto exchanges do to comply with kyc, aml and cft regulations. https://cointelegraph.com/news/what-crypto-exchanges-do-to-comply-with-kyc-aml-and-cft-regulations. [Online, Accessed January 11, 2020].

[3] Ahamad, S., Nair, M., Varghese, B., 2013. A survey on crypto currencies, in: 4th International Conference on Advances in Computer Science, AETACS, Citeseer. pp. 42–48.

[4] Alessandretti, L., ElBahrawy, A., Aiello, L.M., Baronchelli, A., 2018. Anticipating cryptocurrency prices using machine learning. Complexity 2018.

[5] Antipova, V., 2019. Building and testing global investment portfolios using alternative asset classes. Master's thesis. Vytautas Magnus University. Lithuania.

[6] Atsalakis, G.S., Atsalaki, I.G., Pasiouras, F., Zopounidis, C., 2019. Bitcoin price forecasting with neuro-fuzzy techniques. European Journal of Operational Research 276, 770–780.

[7] Attanasio, G., Cagliero, L., Garza, P., Baralis, E., 2019. Quantitative cryptocurrency trading: exploring the use of machine learning techniques, in: Proceedings of the 5th Workshop on Data Science for Macro-modeling with Financial and Economic Datasets, ACM. p. 1.

[8] Authority, F.C., 2019. Contract for differences. https://www.fca.org.uk/firms/contracts-for-difference. [Online, Accessed January 29, 2020].

[9] Bach, W.G., Kasper, L., 2018. On Machine Learning Based Cryptocurrency Trading. Master's thesis. Aalborg University. Denmark.

[10] Badenhorst, J.J., et al., 2019. Effect of Bitcoin spot and derivative trading volumes on price volatility. Ph.D. thesis. University of Pretoria.

[11] Bai, S., Robinson, F., 2019. Automated Triangular Arbitrage:: A Trading Algorithm for Foreign Exchange on a Cryptocurrency Market. Bachelor's thesis. KTH Royal Institute of Technology. Sweden.

[12] BAKKT, 2020a. Bakkt markets. https://www.bakkt.com/index. [Online, Accessed February 11, 2020].

[13] BAKKT, 2020b. Bakkt terms of use. https://www.bakkt.com/terms-of-use. [Online, Accessed: February 11, 2020].

[14] Barnwal, A., Bharti, H., Ali, A., Singh, V., 2019. Stacking with neural network for cryptocurrency investment. arXiv preprint arXiv:1902.07855 .

[15] Bartolucci, S., Destefanis, G., Ortu, M., Uras, N., Marchesi, M., Tonelli, R., 2019. The butterfly affect: Impact of development practices on cryptocurrency prices .

[16] Baur, D.G., Dimpfl, T., Kuck, K., 2018. Bitcoin, gold and the us dollar–a replication and extension. Finance Research Letters 25, 103–110.

[17] Bauriya, A., Tikone, A., Nandgaonkar, P., Sakure, K.S., 2019. Real-time cryptocurrency trading system. International Research Journal of Engineering and Technology (IRJET) 06.

[18] Bedi, P., Nashier, T., 2020. On the investment credentials of bitcoin: A cross-currency perspective. Research in International Business and Finance 51, 101087.

[19] Bell, T., 2016. Bitcoin trading agents. University of Southampton .

[20] Ben-Akiva, M., McFadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., Bolduc, D., Boersch-Supan, A., Brownstone, D., Bunch, D.S., et al., 2002. Hybrid choice models: progress and challenges. Marketing Letters 13, 163–175.

[21] Beneki, C., Koulis, A., Kyriazis, N.A., Papadamou, S., 2019. Investigating volatility transmission and hedging properties between bitcoin and ethereum. Research in International Business and Finance 48, 219–227.

[22] Binance, 2020a. Binance partners with coinfirm to protect the global cryptocurrency economy and ensure compliance with fatf aml rules. https://www.binance.com/en/blog/386484403820867584/Binance-Partners-with-Coinfirm-to-Protect-the-Global-Cryptocurrency-Economy-and-Ensure-Compliance-with-FATF-AML-Rules. [Online, Accessed February 11, 2020].

[23] Binance, 2020b. Binance review 2020: Pros, cons, fees, features, and safety. https://insidebitcoins.com/cryptocurrency-exchanges/binance-review/. [Online, Accessed: February 11, 2020].

[24] Bitfinex, 2020a. Bitfinex markets. https://www.bitfinex.com/. [Online, Accessed: February 11, 2020].

[25] Bitfinex, 2020b. Bitfinex terms of service. https://www.bitfinex.com/legal/terms. [Online, Accessed: February 11, 2020].

[26] Bitfinex, 2020c. New york court rules that state attorney has jurisdiction over bitfinex. https://cointelegraph.com/news/new-york-court-rules-that-state-attorney-has-jurisdiction-over-bitfinex. [Online, Accessed February 11, 2020].

[27] Bitmex, 2020a. Beginner's guide to bitmex: Complete review. https://blockonomi.com/bitmex-review/. [Online, Accessed: February 11, 2020].

[28] Bitmex, 2020b. Bitmex. https://www.bitmex.com/register. [Online, Accessed: February 11, 2020].

[29] Bitstamp, 2020a. Bitstamp review 2020. https://www.fxempire.com/crypto/exchange/bitstamp/review. [Online, Accessed: February 11, 2020].

[30] Bitstamp, 2020b. Bitstamp who we are. https://www.bitstamp.net/about-us/. [Online, Accessed: February 11, 2020].

[31] Bitstamp, 2020c. Terms of use. https://www.bitstamp.net/terms-of-use/sa. [Online, Accessed February 11, 2020].

[32] Blackbird, 2020. Blackbird bitcoin arbitrage: a long/short market-neutral strategy. https://github.com/butor/blackbird. [Online, Accessed: January 26, 2020].

[33] Bloomberg, 2020. Coinbase inc. https://www.bloomberg.com/profile/company/0776164D:US. [Online, Accessed: February 11, 2020].

[34] Bouri, E., Jalkh, N., Molnár, P., Roubaud, D., 2017. Bitcoin for energy commodities before and after the december 2013 crash: diversifier, hedge or safe haven? Applied Economics 49, 5063–5073.

[35] Bouri, E., Lau, C.K.M., Lucey, B., Roubaud, D., 2019a. Trading volume and the predictability of return and volatility in the cryptocurrency market. Finance Research Letters 29, 340–346.

[36] Bouri, E., Shahzad, S.J.H., Roubaud, D., 2019b. Co-explosivity in the cryptocurrency market. Finance Research Letters 29, 178–183.

[37] Brauneis, A., Mestel, R., 2019. Cryptocurrency-portfolios in a mean-variance framework. Finance Research Letters 28, 259–264.

[38] van den Broek, L., Sharif, Z., 2018. Cointegration-based pairs trading framework with application to the cryptocurrency market .

[39] Brunnermeier, M.K., Oehmke, M., 2013. Bubbles, financial crises, and systemic risk, in: Handbook of the Economics of Finance. Elsevier. volume 2, pp. 1221–1288.

[40] Bu, S.J., Cho, S.B., 2018. Learning optimal q-function using deep boltzmann machine for reliable trading of cryptocurrency, in: International Conference on Intelligent Data Engineering and Automated Learning, Springer. pp. 468–480.

[41] Calo, B., Johnson, W., 2002. Global trading system. US Patent App. 09/769,036.

[42] Capfolio, 2020. Capfolio cryptocurrency trading platform. https://www.capfol.io/. [Online, Accessed: January 26, 2020].

[43] Caporale, G.M., Gil-Alana, L., Plastun, A., 2018. Persistence in the cryptocurrency market. Research in International Business and Finance 46, 141–148.

[44] Caporale, G.M., Plastun, A., 2018. Price Overreactions in the Cryptocurrency Market. CESifo Working Paper 6861. Munich. URL: http://hdl.handle.net/10419/174984.

[45] Caporale, G.M., Plastun, A., 2019. The day of the week effect in the cryptocurrency market. Finance Research Letters 31.

[46] Caporin, M., McAleer, M., 2012. Do we really need both bekk and dcc? a tale of two multivariate garch models. Journal of Economic Surveys 26, 736–751.

[47] Castro, J.G., Tito, E.A.H., Brandão, L.E.T., Gomes, L.L., 2019. Crypto-assets portfolio optimization under the omega measure. The Engineering Economist , 1–21.

[48] Catalyst, 2020. An algorithmic trading library for crypto-assets in python. https://github.com/enigmampc/catalyst. [Online, Accessed: January 26, 2020].

[49] CBOE, 2020a. Cboe history. http://www.cboe.com/aboutcboe/history. [Online, Accessed: February 11, 2020].

[50] CBOE, 2020b. Cboe products. https://www.cboe.com. [Online, Accessed: February 11, 2020].

[51] CBOE, 2020c. Cfe regulation. https://www.cboe.com/aboutcboe/legal-regulatory/departmental-overviews/cfe-regulation. [Online, Accessed February 11, 2020].

[52] Ccxt, 2020. Ccxt – cryptocurrency exchange trading library. https://github.com/ccxt/ccxt. [Online, Accessed: January 26, 2020].

[53] Chaim, P., Laurini, M.P., 2018. Volatility and return jumps in bitcoin. Economics Letters 173, 158–163.

[54] Chaim, P., Laurini, M.P., 2019. Nonlinear dependence in cryptocurrency markets. The North American Journal of Economics and Finance 48, 32–47.

[55] Chang, C.C., Hsieh, P.F., Wang, Y.H., 2015. Sophistication, sentiment, and misreaction. Journal of Financial and Quantitative Analysis 50, 903–928.

[56] Cheah, E.T., Fry, J., 2015. Speculative bubbles in bitcoin markets? an empirical investigation into the fundamental value of bitcoin. Economics Letters 130, 32–36.

[57] Cheng, J., Dong, L., Lapata, M., 2016. Long short-term memory-networks for machine reading. arXiv preprint arXiv:1601.06733 .

[58] Cheung, A., Roca, E., Su, J.J., 2015. Crypto-currency bubbles: an application of the phillips–shi–yu (2013) methodology on mt. gox bitcoin prices. Applied Economics 47, 2348–2358.

[59] Choi, B., 2012. ARMA model identification. Springer Science & Business Media.

[60] Chung, J., Gulcehre, C., Cho, K., Bengio, Y., 2014. Empirical evaluation of gated recurrent neural networks on sequence modeling. arXiv preprint arXiv:1412.3555 .

[61] CME, 2020a. Cme cryptocurrency products. https://www.cmegroup.com/trading/cryptocurrency-indices.html. [Online, Accessed: February 11, 2020].

[62] CME, 2020b. Cme group rules and regulation overview. https://www.cmegroup.com/education/courses/market-regulation/overview/cme-group-rules-and-regulation-overview.html. [Online, Accessed February 11, 2020].

[63] CME, 2020c. Cme groups overview. https://www.cmegroup.com/company/history/. [Online, Accessed: February 11, 2020].

[64] Cocco, L., Concas, G., Marchesi, M., 2017. Using an artificial financial market for studying a cryptocurrency market. Journal of Economic Interaction and Coordination 12, 345–365.

[65] Coinbase, 2020a. Coinbase supported cryptocurrencies. https://help.coinbase.com/en/coinbase/getting-started/general-crypto-education/supported-cryptocurrencies.html. [Online, Accessed: February 11, 2020].

[66] Coinbase, 2020b. Our path to listing sec-regulated crypto securities. https://blog.coinbase.com/our-path-to-listing-sec-regulated-crypto-securities-a1724e13bb5a. [Online, Accessed February 11, 2020].

[67] CoinMaketCap, 2019. Top 100 cryptocurrencies by market capitalization URL: https://coinmarketcap.com/.

[68] Coinmarketcap, 2020. Percentage of total market capitalization. https://coinmarketcap.com/charts/}dominance-percentage. [Online, Accessed January 11, 2020].

[69] Colianni, S., Rosales, S., Signorotti, M., 2015. Algorithmic trading of cryptocurrency based on twitter sentiment analysis. CS229 Project , 1–5.

[70] Conrad, C., Custovic, A., Ghysels, E., 2018. Long-and short-term cryptocurrency volatility components: A garch-midas analysis. Journal of Risk and Financial Management 11, 23.

[71] Corbet, S., Eraslan, V., Lucey, B., Sensoy, A., 2019a. The effectiveness of technical trading rules in cryptocurrency markets. Finance Research Letters 31, 32–37.

[72] Corbet, S., Lucey, B., Urquhart, A., Yarovaya, L., 2019b. Cryptocurrencies as a financial asset: A systematic analysis. International Review of Financial Analysis 62, 182–199.

[73] Corbet, S., Lucey, B., Yarovaya, L., 2018a. Datestamping the bitcoin and ethereum bubbles. Finance Research Letters 26, 81–88.

[74] Corbet, S., Meegan, A., Larkin, C., Lucey, B., Yarovaya, L., 2018b. Exploring the dynamic relationships between cryptocurrencies and other financial assets. Economics Letters 165, 28–34.

[75] Cryptosignal, 2020. Automated crypto trading and technical analysis (ta) bot. https://github.com/CryptoSignal/crypto-signal. [Online, Accessed: January 26, 2020].

[76] Ctubio, 2020. Ctubio - cryptocurrency trading bot. https://github.com/ctubio/Krypto-trading-bot. [Online, Accessed: January 26, 2020].

[77] Diebold, F.X., Yılmaz, K., 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. Journal of Econometrics 182, 119–134.

[78] Domínguez, M.A., Lobato, I.N., 2003. Testing the martingale difference hypothesis. Econometric Reviews 22, 351–377.

[79] Doran, M.D., 2014. A forensic look at bitcoin cryptocurrency. Ph.D. thesis. Utica College.

[80] Dyhrberg, A.H., 2016. Bitcoin, gold and the dollar–a garch volatility analysis. Finance Research Letters 16, 85–92.

[81] Easley, D., Engle, R.F., O'Hara, M., Wu, L., 2008. Time-varying arrival rates of informed and uninformed trades. Journal of Financial Econometrics 6, 171–207.

[82] Elliott, R.J., Van Der Hoek*, J., Malcolm, W.P., 2005. Pairs trading. Quantitative Finance 5, 271–276.

[83] Engle, R., 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business & Economic Statistics 20, 339–350.

[84] Engle, R.F., Kroner, K.F., 1995. Multivariate simultaneous generalized arch. Econometric theory 11, 122–150.

[85] Enoksen, F.A., Landsnes, C.J., 2019. What Can Predict Bubbles in Cryptocurrency Prices? Master's thesis. University of Stavanger, Norway.

[86] Escanciano, J.C., Velasco, C., 2006. Generalized spectral tests for the martingale difference hypothesis. Journal of Econometrics 134,

151–185.
[87] Estalayo, I., Del Ser, J., Osaba, E., Bilbao, M.N., Muhammad, K., Gálvez, A., Iglesias, A., 2019. Return, diversification and risk in cryptocurrency portfolios using deep recurrent neural networks and multi-objective evolutionary algorithms, in: 2019 IEEE Congress on Evolutionary Computation (CEC), IEEE. pp. 755–761.
[88] Fang, F., Chung, W., Ventre, C., Basios, M., Kanthan, L., Li, L., Wu, F., 2019. Ascertaining price formation in cryptocurrency markets with deeplearning. arXiv preprint arXiv:2003.00803 .
[89] Fantazzini, D., Zimin, S., 2019. A multivariate approach for the simultaneous modelling of market risk and credit risk for cryptocurrencies. Journal of Industrial and Business Economics , 1–51.
[90] Feng, W., Wang, Y., Zhang, Z., 2018. Informed trading in the bitcoin market. Finance Research Letters 26, 63–70.
[91] Fil, M., 2019. Pairs trading in cryptocurrency markets .
[92] Flori, A., 2019. News and subjective beliefs: A bayesian approach to bitcoin investments. Research in International Business and Finance 50, 336–356.
[93] Fretrade, 2020. Freqtrade. https://github.com/freqtrade/freqtrade. [Online, Accessed: January 26, 2020].
[94] Friedl, M.A., Brodley, C.E., 1997. Decision tree classification of land cover from remotely sensed data. Remote sensing of environment 61, 399–409.
[95] Friedman, J., Tibshirani, R., 1984. The monotone smoothing of scatterplots. Technometrics 26, 243–250.
[96] Friedman, J.H., 2001. Greedy function approximation: a gradient boosting machine. Annals of statistics , 1189–1232.
[97] Gandal, N., Halaburda, H., 2014. Competition in the cryptocurrency market. CEPR Discussion Paper No. DP10157.
[98] Garcia, D., Schweitzer, F., 2015. Social signals and algorithmic trading of bitcoin. Royal Society open science 2, 150288.
[99] Garza, P., 2019. Formal automatic trading in the cryptocurrency era. Ph.D. thesis. Politecnico di Torino.
[100] Gatev, E., Goetzmann, W.N., Rouwenhorst, K.G., 2006. Pairs trading: Performance of a relative-value arbitrage rule. The Review of Financial Studies 19, 797–827.
[101] Gerritsen, D.F., Bouri, E., Ramezanifar, E., Roubaud, D., 2019. The profitability of technical trading rules in the bitcoin market. Finance Research Letters .
[102] Golang, 2020. A golang implementation of a console-based trading bot for cryptocurrency exchanges. https://github.com/saniales/golang-crypto-trading-bot. [Online, Accessed: January 26, 2020].
[103] Grayblock, 2018. Elliptic-curve cryptography. https://medium.com/coinmonks/elliptic-curve-cryptography-6de8fc748b8b. [Online, Accessed December 29, 2019].
[104] Griffin, J.M., Shams, A., 2019. Is bitcoin really un-tethered? Available at SSRN 3195066 .
[105] Gu, S., Lillicrap, T., Sutskever, I., Levine, S., 2016. Continuous deep q-learning with model-based acceleration, in: International Conference on Machine Learning, pp. 2829–2838.
[106] Guo, T., Bifet, A., Antulov-Fantulin, N., 2018. Bitcoin volatility forecasting with a glimpse into buy and sell orders, in: 2018 IEEE International Conference on Data Mining (ICDM), IEEE. pp. 989–994.
[107] Ha, S., Moon, B.R., 2018. Finding attractive technical patterns in cryptocurrency markets. Memetic Computing 10, 301–306.
[108] Hale, G., Krishnamurthy, A., Kudlyak, M., Shultz, P., et al., 2018. How futures trading changed bitcoin prices. FRBSF Economic Letter 12.
[109] Hansel, D., 2018. Cryptocurrency trading: How to make money by trading bitcoin and other cryptocurrency (volume 2) .
[110] Harwick, C., 2016. Cryptocurrency and the problem of intermediation. The Independent Review 20, 569–588.
[111] Henderson, P., Islam, R., Bachman, P., Pineau, J., Precup, D., Meger, D., 2018. Deep reinforcement learning that matters, in: Thirty-Second AAAI Conference on Artificial Intelligence.
[112] Hileman, G., Rauchs, M., 2017. Global cryptocurrency benchmarking study. Cambridge Centre for Alternative Finance 33.
[113] Holmes, G., Donkin, A., Witten, I.H., 1994. Weka: A machine learning workbench, in: Proceedings of ANZIIS'94-Australian New Zealnd Intelligent Information Systems Conference, IEEE. pp. 357–361.
[114] Hrytsiuk, P., Babych, T., Bachyshyna, L., 2019. Cryptocurrency portfolio optimization using value-at-risk measure, in: Strategies, Models and Technologies of Economic Systems Management (SMTESM 2019), Atlantis Press.
[115] Hudson, R., Urquhart, A., 2019. Technical analysis and cryptocurrencies. Available at SSRN 3387950 .
[116] Hultman, H., 2018. Volatility Forecasting An Empirical Study on Bitcoin Using Garch and Stochastic Volatility models. Master's thesis. Lund University. Sweden.
[117] Hutto, C.J., Gilbert, E., 2014. Vader: A parsimonious rule-based model for sentiment analysis of social media text, in: Eighth international AAAI conference on weblogs and social media.
[118] Hwang, S., Salmon, M., 2004. Market stress and herding. Journal of Empirical Finance 11, 585–616.
[119] Ji, Q., Bouri, E., Lau, C.K.M., Roubaud, D., 2019. Dynamic connectedness and integration in cryptocurrency markets. International Review of Financial Analysis 63, 257–272.
[120] Jiang, Z., Liang, J., 2017. Cryptocurrency portfolio management with deep reinforcement learning, in: 2017 Intelligent Systems Conference (IntelliSys), IEEE. pp. 905–913.
[121] Jianliang, M., Haikun, S., Ling, B., 2009. The application on intrusion detection based on k-means cluster algorithm, in: 2009 International Forum on Information Technology and Applications, IEEE. pp. 150–152.
[122] Juchli, M., 2018. Limit order placement optimization with Deep Reinforcement Learning: Learning from patterns in cryptocurrency market data. Master's thesis. TU Delft Electrical Engineering. Netherlands.
[123] Kajtazi, A., Moro, A., 2019. The role of bitcoin in well diversified portfolios: A comparative global study. International Review of Financial Analysis 61, 143–157.
[124] Kakushadze, Z., 2016. 101 formulaic alphas. Wilmott 2016, 72–81.
[125] Kakushadze, Z., 2018. Cryptoasset factor models. Algorithmic Finance , 1–18.
[126] Kalchbrenner, N., Grefenstette, E., Blunsom, P., 2014. A convolutional neural network for modelling sentences. arXiv preprint arXiv:1404.2188 .
[127] Kamrat, S., Suesangiamsakul, N., Marukatat, R., 2018. Technical analysis for cryptocurrency trading on mobile phones, in: 2018 3rd Technology Innovation Management and Engineering Science International Conference (TIMES-iCON), IEEE. pp. 1–4.
[128] Kang, K., Choo, J., Kim, Y., 2019a. Whose opinion matters? analyzing relationships between bitcoin prices and user groups in online community. Social Science Computer Review , 0894439319840716.
[129] Kang, S.H., McIver, R.P., Hernandez, J.A., 2019b. Co-movements between bitcoin and gold: A wavelet coherence analysis. Physica A: Statistical Mechanics and its Applications , 120888.
[130] Kat, H.M., Heynen, R.C., 1994. Volatility prediction: A comparison of the stochastic volatility, garch (1, 1) and egarch (1, 1) models. Journal of Derivatives 2.
[131] Kate, C., 2018. Cryptocurrency trading for beginners: 6-steps action plan to your first investment .
[132] Katsiampa, P., 2019. An empirical investigation of volatility dynamics in the cryptocurrency market. Research in International Business and Finance .
[133] Katsiampa, P., Corbet, S., Lucey, B.M., 2018a. Volatility spillover effects in leading cryptocurrencies: A bekk-mgarch analysis. Available at SSRN 3232912 .
[134] Katsiampa, P., Gkillas, K., Longin, F., 2018b. Cryptocurrency market activity during extremely volatile periods URL: https://ssrn.com/abstract=3220781, doi:https://dx.doi.org/10.2139/ssrn.3220781.
[135] Kaufman, P.J., 2013. Trading Systems and Methods,+ Website. vol-

ume 591. John Wiley & Sons.

[136] Khuntia, S., Pattanayak, J., 2018. Adaptive market hypothesis and evolving predictability of bitcoin. Economics Letters 167, 26–28.

[137] Kim, K., Kim, J., Rinaldo, A., 2018. Time series featurization via topological data analysis: an application to cryptocurrency trend forecasting. arXiv preprint arXiv:1812.02987 .

[138] Kim, Y.B., Kim, J.G., Kim, W., Im, J.H., Kim, T.H., Kang, S.J., Kim, C.H., 2016. Predicting fluctuations in cryptocurrency transactions based on user comments and replies. PloS one 11, e0161197.

[139] Kondor, D., Csabai, I., Szule, J., Psfai, M., Vattay, G., 2014. Inferring the interplay between network structure and market effects in bitcoin. New Journal of Physics 16, 125003. URL: https://doi.org/10.1088%2F1367-2630%2F16%2F12%2F125003, doi:10.1088/1367-2630/16/12/125003.

[140] Krafft, P.M., Della Penna, N., Pentland, A.S., 2018. An experimental study of cryptocurrency market dynamics, in: Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, ACM. p. 605.

[141] Kristoufek, L., 2013. Bitcoin meets google trends and wikipedia: Quantifying the relationship between phenomena of the internet era. Scientific reports 3, 3415.

[142] Kurbucz, M.T., 2019. Predicting the price of bitcoin by the most frequent edges of its transaction network. Economics Letters 184, 108655.

[143] Kutner, M.H., Nachtsheim, C.J., Neter, J., Li, W., et al., 2005. Applied linear statistical models. volume 5. McGraw-Hill Irwin New York.

[144] Kwon, D.H., Kim, J.B., Heo, J.S., Kim, C.M., Han, Y.H., 2019. Time series classification of cryptocurrency price trend based on a recurrent lstm neural network. Journal of Information Processing Systems 15.

[145] Kyriazis, N.A., 2019. A survey on efficiency and profitable trading opportunities in cryptocurrency markets. Journal of Risk and Financial Management 12, 67.

[146] Lamon, C., Nielsen, E., Redondo, E., 2017. Cryptocurrency price prediction using news and social media sentiment. SMU Data Sci. Rev 1, 1–22.

[147] Lawrence, S., Giles, C.L., Tsoi, A.C., Back, A.D., 1997. Face recognition: A convolutional neural-network approach. IEEE transactions on neural networks 8, 98–113.

[148] Leclair, E.M., 2018. Herding in the cryptocurrency market. Econ 5029 final research. Carleton University. Canada.

[149] Lee, T.H., Yang, W., 2014. Granger-causality in quantiles between financial markets: Using copula approach. International Review of Financial Analysis 33, 70–78.

[150] Li, T.R., Chamrajnagar, A., Fong, X., Rizik, N., Fu, F., 2019. Sentiment-based prediction of alternative cryptocurrency price fluctuations using gradient boosting tree model. Frontiers in Physics 7, 98.

[151] Liaw, A., Wiener, M., et al., 2002. Classification and regression by randomforest. R news 2, 18–22.

[152] Liu, W., 2019. Portfolio diversification across cryptocurrencies. Finance Research Letters 29, 200–205.

[153] Localbtc, 2020. Localbitcoins purchasing online. https://localbitcoins.com. [Online, Accessed: January 11, 2020].

[154] Lucarelli, G., Borrotti, M., 2019. A deep reinforcement learning approach for automated cryptocurrency trading, in: IFIP International Conference on Artificial Intelligence Applications and Innovations, Springer. pp. 247–258.

[155] Luu Duc Huynh, T., 2019. Spillover risks on cryptocurrency markets: A look from var-svar granger causality and student copulas. Journal of Risk and Financial Management 12, 52.

[156] Madan, I., Saluja, S., Zhao, A., 2015. Automated bitcoin trading via machine learning algorithms. URL: http://cs229. stanford. edu/proj2014/Isaac% 20Madan 20.

[157] Makarov, I., Schoar, A., 2020. Trading and arbitrage in cryptocurrency markets. Journal of Financial Economics 135, 293–319.

[158] Maltatoday, 2020. Why world leader crypto exchange binance moved to malta. https://www.maltatoday.com.mt/business/business_news/93170/why_world_leader_crypto_exchange_binance_moved_to_malta}.XlKZ8Gj7Q2x. [Online, Accessed: February 11, 2020].

[159] Markowitz, H., 1952. Portfolio selection. The Journal of Finance 7, 77–91.

[160] McNally, S., 2016. Predicting the price of Bitcoin using Machine Learning. Ph.D. thesis. Dublin, National College of Ireland.

[161] McNally, S., Roche, J., Caton, S., 2018. Predicting the price of bitcoin using machine learning, in: 2018 26th Euromicro International Conference on Parallel, Distributed and Network-based Processing (PDP), IEEE. pp. 339–343.

[162] Meunier, S., 2018. Blockchain 101: What is blockchain and how does this revolutionary technology work?, in: Transforming Climate Finance and Green Investment with Blockchains. Elsevier, pp. 23–34.

[163] Mikolov, T., Kombrink, S., Burget, L., Černockỳ, J., Khudanpur, S., 2011. Extensions of recurrent neural network language model, in: 2011 IEEE international conference on acoustics, speech and signal processing (ICASSP), IEEE. pp. 5528–5531.

[164] MIT, 2015. Bitcoin network dataset. https://senseable2015-6.mit.edu/bitcoin. [Online, Accessed January 11, 2020].

[165] Molina, J., 2019. Develop your crypto-trading system using plain logic, part 1. URL: https://medium.com/swlh/develop-your-crypto-trading-system-using-plain-logic-part-1-caac02f0a37d.

[166] Mukhopadhyay, U., Skjellum, A., Hambolu, O., Oakley, J., Yu, L., Brooks, R., 2016. A brief survey of cryptocurrency systems, in: 2016 14th annual conference on privacy, security and trust (PST), IEEE. pp. 745–752.

[167] Nakamoto, S., 2009. Bitcoin open source implementation of p2p currency. P2P foundation 18.

[168] Nakano, M., Takahashi, A., Takahashi, S., 2018. Bitcoin technical trading with artificial neural network. Physica A: Statistical Mechanics and its Applications 510, 587–609.

[169] Narayanan, A., Bonneau, J., Felten, E., Miller, A., Goldfeder, S., 2016. Bitcoin and cryptocurrency technologies: a comprehensive introduction. Princeton University Press.

[170] Nasir, M.A., Huynh, T.L.D., Nguyen, S.P., Duong, D., 2019. Forecasting cryptocurrency returns and volume using search engines. Financial Innovation 5, 2.

[171] Neter, J., Kutner, M.H., Nachtsheim, C.J., Wasserman, W., 1996. Applied linear statistical models. volume 4. Irwin Chicago.

[172] Ng, A.Y., Jordan, M.I., 2002. On discriminative vs. generative classifiers: A comparison of logistic regression and naive bayes, in: Advances in neural information processing systems, pp. 841–848.

[173] Nomics, 2020. Top cryptocurrency exchanges list. https://nomics.com/exchanges. [Online, Accessed: January 11, 2020].

[174] Ogorevc, M., 2019. Cryptocurrency as money: A trading strategy solution. Available at SSRN 3436041 .

[175] Omane-Adjepong, M., Alagidede, I.P., 2019. Multiresolution analysis and spillovers of major cryptocurrency markets. Research in International Business and Finance 49, 191–206.

[176] Omane-Adjepong, M., Alagidede, P., Akosah, N.K., 2019. Wavelet time-scale persistence analysis of cryptocurrency market returns and volatility. Physica A: Statistical Mechanics and its Applications 514, 105–120.

[177] Patil, A.P., Akarsh, T., Parkavi, A., 2018. A study of opinion mining and data mining techniques to analyse the cryptocurrency market, in: 2018 3rd International Conference on Computational Systems and Information Technology for Sustainable Solutions (CSITSS), IEEE. pp. 198–203.

[178] Păuna, C., 2018. Arbitrage trading systems for cryptocurrencies. design principles and server architecture. Informatica Economica 22, 35–42.

[179] Persson, S., Slottje, A., Shaw, I., 2018. Hybrid Autoregressive-Recurrent Neural Network Architecture for Algorithmic Trading of Cryptocurrencies. Cs230 deep learning thesis. Stanford University.

[180] Phaladisailoed, T., Numnonda, T., 2018. Machine learning models

comparison for bitcoin price prediction, in: 2018 10th International Conference on Information Technology and Electrical Engineering (ICITEE), IEEE. pp. 506–511.
[181] Phillips, P.C., Shi, S., Yu, J., 2015a. Testing for multiple bubbles: Historical episodes of exuberance and collapse in the s&p 500. International economic review 56, 1043–1078.
[182] Phillips, P.C., Shi, S., Yu, J., 2015b. Testing for multiple bubbles: Limit theory of real-time detectors. International Economic Review 56, 1079–1134.
[183] Phillips, R.C., Gorse, D., 2017. Predicting cryptocurrency price bubbles using social media data and epidemic modelling, in: 2017 IEEE Symposium Series on Computational Intelligence (SSCI), IEEE. pp. 1–7.
[184] Phillips, R.C., Gorse, D., 2018a. Cryptocurrency price drivers: Wavelet coherence analysis revisited. PloS one 13, e0195200.
[185] Phillips, R.C., Gorse, D., 2018b. Mutual-excitation of cryptocurrency market returns and social media topics, in: Proceedings of the 4th International Conference on Frontiers of Educational Technologies, ACM. pp. 80–86.
[186] Poloniex, 2020. Poloniex markets. https://poloniex.com/. [Online, Accessed: February 11, 2020].
[187] Rane, P.V., Dhage, S.N., 2019. Systematic erudition of bitcoin price prediction using machine learning techniques, in: 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS), IEEE. pp. 594–598.
[188] Rebane, J., Karlsson, I., Denic, S., Papapetrou, P., 2018. Seq2seq rnns and arima models for cryptocurrency prediction: A comparative study. SIGKDD Fintech 18.
[189] Rish, I., et al., 2001. An empirical study of the naive bayes classifier, in: IJCAI 2001 workshop on empirical methods in artificial intelligence, pp. 41–46.
[190] Rose, C., 2015. The evolution of digital currencies: Bitcoin, a cryptocurrency causing a monetary revolution. International Business & Economics Research Journal (IBER) 14, 617–622.
[191] S., J., 2018. How do blockchain mining and transactions work explained in 7 simple steps. https://blog.goodaudience.com/how-a-miner-adds-transactions-to-the-blockchain-in-seven-steps-856053271476. [Online, Accessed: January 26, 2020].
[192] Salakhutdinov, R., Hinton, G., 2009. Deep boltzmann machines, in: Artificial intelligence and statistics, pp. 448–455.
[193] Shanaev, S., Sharma, S., Ghimire, B., Shuraeva, A., 2020. Taming the blockchain beast? regulatory implications for the cryptocurrency market. Research in International Business and Finance 51, 101080.
[194] Sharma, S., Krishma, N., Raina, E., 2017. Survey paper on cryptocurrency. International Journal of Scientific Research in Computer Science, Engineering and Information Technology Vol. 2 Issue 3, 307–310.
[195] Siaminos, G., 2019. Predicting the value of cryptocurrencies using machine learning time series analysis time series analysis time .
[196] Sigaki, H.Y., Perc, M., Ribeiro, H.V., 2019. Clustering patterns in efficiency and the coming-of-age of the cryptocurrency market. Scientific reports 9, 1440.
[197] Sirignano, J., Cont, R., 2019. Universal features of price formation in financial markets: perspectives from deep learning. Quantitative Finance 19, 1449–1459.
[198] Smuts, N., 2019. What drives cryptocurrency prices?: An investigation of google trends and telegram sentiment. ACM SIGMETRICS Performance Evaluation Review 46, 131–134.
[199] Sriram, A., Jun, H., Satheesh, S., Coates, A., 2017. Cold fusion: Training seq2seq models together with language models. arXiv preprint arXiv:1708.06426 .
[200] Stocksharp, 2020. Stocksharp - trading platform. https://github.com/StockSharp/StockSharp. [Online, Accessed: January 26, 2020].
[201] Stuerner, P., 2019. Algorithmic Cryptocurrency Trading. Ph.D. thesis. Ulm University.
[202] Sun, J., Zhou, Y., Lin, J., 2019. Using machine learning for cryptocurrency trading, in: 2019 IEEE International Conference on Industrial Cyber Physical Systems (ICPS), IEEE. pp. 647–652.
[203] Sutton, R.S., Barto, A.G., et al., 1998. Introduction to reinforcement learning. volume 135. MIT press Cambridge.
[204] Sze, V., Chen, Y.H., Yang, T.J., Emer, J.S., 2017. Efficient processing of deep neural networks: A tutorial and survey. Proceedings of the IEEE 105, 2295–2329.
[205] Tapscott, D., Tapscott, A., 2016. Blockchain revolution: how the technology behind bitcoin is changing money, business, and the world. Penguin.
[206] TradingstrategyGuides, 2019a. Eos cryptocurrency trading strategy–turtle soup pattern. https://tradingstrategyguides.com/eos-cryptocurrency-trading-strategy/. [Online, Accessed January 29, 2020].
[207] TradingstrategyGuides, 2019b. Free omni cryptocurrency strategy–amazing gann box. https://tradingstrategyguides.com/free-omni-cryptocurrency-strategy/. [Online, Accessed January 29, 2020].
[208] TradingstrategyGuides, 2019c. Iota cryptocurrency strategy–busted double top pattern. https://tradingstrategyguides.com/iota-cryptocurrency-strategy/. [Online, Accessed January 29, 2020].
[209] TradingstrategyGuides, 2019d. Nem (xem) cryptocurrency strategy–momentum pinball setup. https://tradingstrategyguides.com/nem-xem-cryptocurrency-strategy/. [Online, Accessed January 29, 2020].
[210] TradingstrategyGuides, 2019e. Tether trading strategy–bottom rotation trading. https://tradingstrategyguides.com/tether-trading-strategy/. [Online, Accessed January 29, 2020].
[211] TradingView, 2020. Total crypto market capitalization and volume. https://www.tradingview.com/markets/cryptocurrencies/global-charts/. [Online, Accessed February 23, 2020].
[212] Trucíos, C., Tiwari, A.K., Alqahtani, F., 2019. Value-at-risk and expected shortfall in cryptocurrencies' portfolio: A vine copula-based approach. Available at SSRN 3441892 .
[213] Vidal-Tomás, D., Ibáñez, A.M., Farinós, J.E., 2019. Herding in the cryptocurrency market: Cssd and csad approaches. Finance Research Letters 30, 181–186.
[214] Virk, D.S., 2017. Prediction of Bitcoin Price using Data Mining. Master's thesis. National College of Ireland.
[215] Vo, A., Yost-Bremm, C., 2018. A high-frequency algorithmic trading strategy for cryptocurrency. Journal of Computer Information Systems , 1–14.
[216] Vogelvang, B., 2005. Econometrics: theory and applications with Eviews. Pearson Education.
[217] Wagstaff, K., Cardie, C., Rogers, S., Schrödl, S., et al., 2001. Constrained k-means clustering with background knowledge, in: Icml, pp. 577–584.
[218] Wang, H., He, D., Ji, Y., 2017. Designated-verifier proof of assets for bitcoin exchange using elliptic curve cryptography. Future Generation Computer Systems .
[219] Wang, L., 2005. Support vector machines: theory and applications. volume 177. Springer Science & Business Media.
[220] Ward, M., 2018. Algorithmic Trading for Cryptocurrencies. Departmental honors thesis. UtahState University. United States.
[221] Weber, P., Wang, F., Vodenska-Chitkushev, I., Havlin, S., Stanley, H.E., 2007. Relation between volatility correlations in financial markets and omori processes occurring on all scales. Physical Review E 76, 016109.
[222] Wohlin, C., 2014. Guidelines for snowballing in systematic literature studies and a replication in software engineering, in: Proceedings of the 18th international conference on evaluation and assessment in software engineering, pp. 1–10.
[223] Xu, Z., Wang, S., Zhu, F., Huang, J., 2017. Seq2seq fingerprint: An unsupervised deep molecular embedding for drug discovery, in: Proceedings of the 8th ACM International Conference on Bioinformatics, Computational Biology, and Health Informatics, pp. 285–294.
[224] Yang, H., 2018. Behavioral anomalies in cryptocurrency markets. Available at SSRN 3174421 URL:

https://ssrn.com/abstract=3174421, doi:https://dx.doi.org/10.2139/ssrn.3174421.

[225] Yaya, O.S., Ogbonna, E.A., Olubusoye, O.E., 2018. How persistent and dependent are pricing of bitcoin to other cryptocurrencies before and after 2017/18 crash? .

[226] Zamuda, A., Crescimanna, V., Burguillo, J.C., Dias, J.M., Wegrzyn-Wolska, K., Rached, I., Gonzlez, H., Senkerik, R., Pop, C., Cioara, T., et al., 2019. Forecasting cryptocurrency value by sentiment analysis: An hpc-oriented survey of the state-of-the-art in the cloud era, in: High-Performance Modelling and Simulation for Big Data Applications. Springer, pp. 325–349.

[227] Żbikowski, K., 2016. Application of machine learning algorithms for bitcoin automated trading, in: Machine Intelligence and Big Data in Industry. Springer, pp. 161–168.

[228] Zemmal, N., Azizi, N., Dey, N., Sellami, M., 2016. Adaptive semi supervised support vector machine semi supervised learning with features cooperation for breast cancer classification. Journal of Medical Imaging and Health Informatics 6, 53–62.

[229] Zhang, S., Yao, L., Sun, A., Tay, Y., 2019. Deep learning based recommender system: A survey and new perspectives. ACM Comput. Surv. 52. URL: https://doi.org/10.1145/3285029, doi:10.1145/3285029.

[230] Zhengyang, W., Xingzhou, L., Jinjin, R., Jiaqing, K., 2019. Prediction of cryptocurrency price dynamics with multiple machine learning techniques, in: Proceedings of the 2019 4th International Conference on Machine Learning Technologies, ACM. pp. 15–19.

[231] Zhou, H., Kalev, P.S., 2019. Algorithmic and high frequency trading in asia-pacific, now and the future. Pacific-Basin Finance Journal 53, 186–207.

[232] Ślepaczuk, R., Zenkova, M., 2018. Robustness of support vector machines in algorithmic trading on cryptocurrency market. Central European Economic Journal 5, 186 – 205.