# Bitcoin Trading is Irrational! An Analysis of the Disposition Effect in Bitcoin

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Investors tend to sell their winning investments and hold onto their losers. This phenomenon, known as the *disposition effect* in the field of behavioural finance, is well-known and its prevalence has been shown in a number of existing markets. But what about new atypical markets like cryptocurrencies? Do investors act as irrationally as in traditional markets? One might suspect this and hypothesise that cryptocurrency sells occur more frequently in positive market conditions and less frequently in negative market conditions. However, there is still no empirical evidence to support this. In this paper, we expand on existing research and empirically investigate the prevalence of the disposition effect in Bitcoin by testing this hypothesis. Our results show that investors are indeed subject to the disposition effect, tending to sell their winning positions too soon and holding on to their losing position for too long. This effect is very prominently evident from the boom and bust year 2017 onwards, confirmed via most of the applied technical indicators. In this study, we show that Bitcoin traders act just as irrationally as traders in other, more established markets.

**Keywords:** Behavioural finance, Prospect theory, Disposition effect, Cryptocurrencies

## 1   Introduction

The *disposition effect* is a well-known phenomenon in behavioural finance and is observed when investors tend to sell their winning investments and hold onto their losers [58]. Its presence has been shown in a wide range of established traditional markets such as the stock market [29], treasury bonds [17] or the real estate market [26,56] to name a few.

However, to the best of our knowledge, no comparable empirical evidence exists for cryptocurrency markets like Bitcoin, which can be considered as being *atypical* compared to established markets: they lack a single central authority, they are still largely unregulated, and they show unusually high volatility [20,21,46,14]. Hence, we formulate the central research question to be answered in this paper as follows:

*Do investors in cryptocurrencies like Bitcoin display a tendency to hold on to losing positions for far too long and sell out their winning positions too soon?*

Recent related research by Baur and Dimpfl [7], who investigated the effect of *fear of missing out* in several cryptocurrency markets, already suggests that there might be a link between volatility and the disposition effect, but does not provide empirical evidence for its existence.

We are therefore approaching this research question by examining and validating this economic pattern at the transaction level [19,50,47]. This is possible in cryptocurrencies, since transaction data is openly available and we can also use a number of methods [39] and tools [31,35] that enable us to investigate the transaction behaviour of economic actors. We are particularly interested in interactions with cryptocurrency exchanges. They play a central role in trading cryptocurrencies because they allow investors to buy and sell cryptocurrencies.

*Contribution* In this paper, we expand on existing research and empirically investigate the prevalence of the disposition effect in Bitcoin. We can formulate our overarching hypothesis as follows:

$H_1$ – *Bitcoin sells occur* **more frequently** *in* **positive** *market conditions and* **less frequently** *in* **negative** *market conditions.*

The corresponding null-hypothesis is defined as $H_0$ – *Bitcoin sells occur less or equally frequently in positive market conditions and more or equally frequently in negative market conditions.*

To test this hypothesis, in Section 3, we first develop a method that allows us to measure *Gains Realised (GR)* compared to *Losses Realised (LR)* when Bitcoins are sold at some cryptocurrency exchange. Our method is inspired by Odean [48], who measured *Proportion of Gains Realised (PGR)* and *Proportion of Losses Realised (PLR)* in individual investment portfolios to test for the disposition effect. As our research investigates a single highly volatile cryptocurrency instead of a portfolio of relatively stable assets in a traditional market, our metrics are non-proportional and computed based on hourly cryptocurrency exchange rates.

Next, in Section 4, we apply this method on the entire blockchain from its inception until December 31st, 2019. We also compute well-established technical indicators such as the *Relative Strength Indicator (RSI)* or *Moving Average Convergence Divergence (MACD)* to allow for comparison. Our empirical result supports the existence of the disposition effect with varying intensity for the Odean metrics, as well as for most of the other technical indicators.

Our results show that cryptocurrency traders act just as irrational as traders in other, more established markets: they sell their winners and hold onto their losers. The boom and bust year 2017 was a pivotal point in the investors trading behaviour. Disposition biased trading significantly increased, attributed to the fact of increased media coverage and publicity, leading to a significant inflow of new investors and an uplift in the number of sell transactions taking place in the market.

For reproducibility, we make our dataset and our implementation openly available at `https://github.com/jschatzmann/CryptoDisposition`.

## 2   Background

We will now explain the principle of the disposition effect as a well-known phenomenon in behavioural finance and briefly consider how it was tested in previous work. In addition, we will give a brief introduction to cryptocurrencies and explain how our measurements expand the existing body of knowledge.

### 2.1   Disposition Effect

Behavioural finance provides the theoretical foundation for this research as it tries to explain the inefficiencies assumed prevalent in the market [9]. Those inefficiencies are described in terms of under- and overreaction to market news and are rooted in the limited attention of (uneducated) investors active in the market. Overreaction occurs when the market reacts too strong or too long to the news, and therefore the adjustment in the opposite direction is required. This phenomenon is also seen in customers' irrational purchasing habits [62] or when investors underreact to news generating a predictable price drift [25].

The disposition effect originates from prospect theory [34] and can be described as *"[...] consistent with the predictions of prospect theory. There is compelling evidence that investors tend to sell their winning investments and to hold onto their losers."* [4, p. 563]. In effect, traders trade too much due to overconfidence.

Statman et al. [58] coined the term *"disposition effect - the predisposition to get-evenitis"* [57, p. 107] and set the aspects of mental accounting, regret or loss aversion, and self-control into a wider theoretical framework. They describe that investors are keeping separate mental investment accounts. The value function of the prospect theory [34, p. 18] stipulates that people are generally more loss-averse, which leads towards the disposition effect when applied on the stock market.

As we will lay out later in Section 2.4, various studies have investigated the disposition effect. Most notably relevant for this research is the study conducted by Terence Odean [48], who investigated 10.000 randomly selected traders of a trading platform and calculated proportion of gains compared to proportion of losses of individual accounts in order to test for the disposition effect. Apart from confirming the presence of the disposition effect, Odean's research provides the theoretical and methodological foundation for the current study.

### 2.2   Technical Analysis and Indicators

Next to the average price indicator inspired by T. Odean [48], we also apply well-known technical analysis (TA) methods and related indicators, which are applied in established, traditional markets. This approach is assumed reasonable as previous research categorises Bitcoin as a speculative asset rather than as any means of payment  [28,8,13,44,68,64,14].

Technical analysis and the underlying technical indicators are used to investigate and examine a stock market from a purely statistical point of view and

therefore plays a fundamental and similarly valuable role in the daily work of financial analysts [37]. Murphy [45] explains the universal valid principles of TA and defines it as follows:

*"Technical analysis is the study of market action, primarily through the use of charts, for the purpose of forecasting future price trends."* [45, p. 1]

The role of TA is to help analysts to determine when various markets have turned in a primary way. The aim is to identify trends at the very earliest stage to maintain the investment posture until indicators determine that the trend has reversed [49]. Key assumptions in TA are built on the principles presented in the literature as follows [12, p. 7]:

1. **Price trends tend to persist**, essentially capturing the momentum concept, stating the supply/demand ratio is slowly varying.
2. **Market action is repetitive**, conceptualising the fact of recurring patterns in price charts that are evolving over time due to the consequence of investors' reactions.

Competitive investors continuously strive to "beat the market". Investors can always find rewards in (financial) markets as the markets themselves are inefficient but to an efficient extent. While doing so, competitive investors push the market toward efficiency but without ever getting there [18]. Bitcoin, like stock markets, also follows the efficient market hypothesis and prices react immediately to publicly announced information [6,16]. Hence we believe Bitcoin is very attractive to speculative and risk-seeking investors using TA with related buy and sell rules. We provide a list of the selected technical indicators and the related trading rules in the appendix in Table 4.

### 2.3 Cryptocurrencies and Cryptoassets

Today, cryptocurrencies are part of a broader cryptoasset ecosystem, which can roughly be divided into *native cryptocurrencies* and *token systems*. Native cryptocurrencies subsume, next to Bitcoin, also so-called *altcoins* (e.g., Litecoin), which are essentially derived from Bitcoin's codebase, and privacy-focused currencies such as Monero or Zcash. Tokens, which represent the other side of the spectrum, can be fungible or non-fungible and are defined and controlled by programs (*smart contracts*) that are executed by distributed blockchain platforms such as Ethereum [11]. In contrast to Bitcoin founded as a non-profit project, many blockchain projects are now driven by for-profit enterprises, which claim to have introduced improvements in speed, robustness, and privacy [67].

Cryptoassetse can be mainly seen as speculative virtual assets, which has also been confirmed by a recent empirical user study [32]. Regarding the three main functions of money, Bitcoin meets the first function, which is *medium of exchange*, but performs poorly as a *unit of account* and as a *store of value*, which are the other two functions [15,69]. This is because cryptoassets experience high

volatility and different trade prices on different exchanges. Further, the most important cryptocurrency Bitcoin is untethered to other fiat currencies, which makes its risk mostly impossible to hedge and poses challenges for proper risk management.

The speculative nature of Bitcoin has also been discussed by Ciaian et al. [15], who compared Bitcoin to conventional currencies and their primary function as money. Their results stipulate that Bitcoins' attractiveness is the main driver for price formation, followed by market forces as the second driver. On the contrary, macrofinancial developments do not determine the Bitcoin price. The study concludes that as long as such speculative investments mainly drive the Bitcoin price, no real competition to fiat currency will emerge. We also followed this point of view and conceived Bitcoin as being a speculative virtual asset rather than a currency.

It is also well-known that cryptoasset ecosystems suffer severe limitations: first, there are technical limitations caused by the underlying blockchain technology, which builds the technical foundation of cryptoassets. It lacks scalability [30], requires relatively high fees for faster transaction confirmation [42], and poses a major ecological problem because of the energy-intensive mining of new coins [38]. A recent study conducted by Stoll et al. [61] estimated the power consumption with 45.8 TWh translating into a carbon emission amount ranging from 22.0 to 22.9 Mt $CO_2$, levels between the carbon footprint of Jordan and Sri Lanka.

Second, the overall system design imposes economic limitations as the computational power invested into the network needs to be balanced in equilibrium to avoid the system's collapse. A collapse could happen as soon as the one-off "stock" benefit of attacking the network is more attractive than its maintenance as the trust that emerges out of the proof-of-work method is costly and limiting [10]. Also, Ford and Böhme [23] investigated a potential attack vector that includes an irrational Byzantine attack. The attacker would lose money within the Bitcoin system but has "hedged" his bet in a financially connected system like Ethereum, hence ultimately making an overall profit. The only possible way to circumvent such arbitrary attacks would be to enforce strong identities, contradicting the main design assumptions of primarily honest and rational behaviour. A similar contradiction of the necessity to redesign the blockchain system to make it compatible with the real-world legal system is brought forward by Schuster [55]. He argues that the necessary design changes would classify the claimed advantages of a blockchain irrelevant, hence from his perspective rendering the blockchain as a whole as "[...] largely pointless" [55, p. 29] and bringing no benefit to the current economic system. This critical view is shared by Roubini, who claims the whole crypto economy as a big heist, "[...]giving rise to an entire criminal industry, comprising unregulated offshore exchanges, paid propagandists, and an army of scammers looking to fleece retail investors[...]"[54, p. 1] and the biggest bubble in human history [63].

Despite strong criticism across academic fields, the cryptoasset economy is still a growing business sector. Hileman and Rauchs [33], who analysed nonpub-

lic data for the global cryptocurrency market (150 different cryptocurrencies, covering 38 countries from five world regions), found that the ecosystem is still a rapidly evolving industry. Since Bitcoin was the first cryptocurrency in place and is still the most used one with the highest market capitalisation [33, p. 16, 18], we measured the disposition effect on the Bitcoin cryptocurrency.

### 2.4 Related Empirical Studies

The disposition effect is a prominent phenomenon in behavioural finance [5]. Various studies investigating the disposition effect on traditional markets have been conducted, covering different scenarios where the disposition effect seems prevalent. Those studies focused on country-specific markets [29,56,59,41,36], trading of risky assets or real estate markets [66,26], trading behaviour of investors [70], and market makers [17]. The empirical evidence of those studies confirms the existence of the disposition effect.

Within the cryptocurrency area, recent research by Baur and Dimpfl [7] on asymmetric volatility in 20 cryptocurrency markets has proposed a link between volatility and disposition effect. The researchers investigated the effect of *fear of missing out* related to uninformed traders in rising market conditions, leading to higher volatility than in falling markets. They argue that the identified asymmetry is in line with the disposition effect, but point out that this effect is very weak for two of the biggest cryptocurrencies, Bitcoin and Ethereum, which are two markets not dominated by uninformed traders. The authors used a model based on (T)GARCH (Generalised Autoregressive Conditional Heteroskedasticity) and quantile regression to estimate volatility. The applied GARCH model sets the primary interest on the (mostly negative) asymmetric volatility indicator $\gamma$. This indicator summarises the trading behaviour after positive and negative shocks where uninformed traders are more likely to trade in upward markets and less in downward markets.

In contrast to the study of Baur and Dimpfl, which focuses on the volatility after positive and negative shocks but does not look into the disposition effect in particular, our research tests the hypothesis of the existence of the disposition effect as the main goal. Our approach focuses on one cryptocurrency and counts the sell activities of investors in upward and downward market conditions without any classification of informed or noninformed traders or positive / negative shock events. The according counts are then evaluated via Students $t$-test to measure the disposition effect.

## 3 Data and Methods

The main goal of our approach is to apply the well-known measurement method for the disposition effect on trading activities in Bitcoin. Since buy and sell trades are nowadays executed mostly via (custodial) service providers such as cryptocurrency exchanges [3], we presuppose that transactions from and to exchanges can be regarded as being proxies for aggregated, individual trading activities and that they reflect the overall market sentiment.

Therefore, we first had to identify cryptocurrency exchanges and extract their transaction history from the Bitcoin blockchain. The exchange addresses used to identify relevant clusters were manually extracted and verified from the walletexplorer[4] page. Next, we had to compute the two key metrics over the set of all exchanges: (i) *LR - losses realised* if cryptocurrency units were sold in a downward-facing market, and (ii) *GR - gains realised* if the sell occurred in an upward-facing market. In the following, we describe how we collected our dataset, how we derived a suitable dataset abstraction, how we identified selling transactions, how we calculated *LR* and *GR* for all selected technical indicators, and how we implemented the overall procedure.

### 3.1 Dataset Collection

We consider the entire Bitcoin blockchain from its inception until December 31th, 2019 (block 610,680)[5] and compute the *Bitcoin Entity Graph* by applying the well-known [53,51] multiple-input clustering heuristics[6]. The underlying intuition is that if two addresses (i.e., A and B) are used as inputs in the same transaction while one of these addresses along with another address (i.e., B and C) are used as inputs in another transaction, then the three addresses (A, B and C) must somehow be controlled by the same entity [40], who conducted both transactions and therefore possesses the private keys corresponding to all three addresses. This heuristic can fail when CoinJoin transactions [43] are taken into account because they combine payments from different spenders that do not necessarily represent one single entity. Being aware of this problem, we filtered these transactions out using detection heuristics similar to those found in the tool BlockSci [35] before applying the multiple-input heuristics.

For further inspecting the real-world identities behind entities, we rely on collaboratively collected TagPacks[7] provisioned by GraphSense. A TagPack is a collection of cryptocurrency attribution tags with associated provenance and categorisation metadata. Possible entity categories are: *Exchange*, *Wallet Service*, *Miner*, *Marketplace*, *Gambling*, *Mixing Service*, or some *Other* service.

### 3.2 Dataset Abstraction

Informally, the resulting data structure is a directed labelled graph with the special characteristics that each node or edge maintains a set of properties. From a data modelling point of view, this is also known as property graph [52], in which a node represents a single real-world entity, and an edge represents the transactions that have taken place between these entities.

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[4] `https://www.walletexplorer.com/`

[5] We test our hypothesis on a yearly and monthly basis and therefore consider only completed years.

[6] For computing the Bitcoin Entity Graph, we used the GraphSense Cryptocurrency Analytics Platform (`https://graphsense.info/`)

[7] `https://github.com/graphsense/graphsense-tagpacks`

Assuming that $A$ is a finite set of addresses, $T$ is the finite set of transactions in Bitcoin within a certain block range, and $C$ is the finite set of entity categories supported by GraphSense TagPacks. We can then formalised this as follows:

**Definition 1 (Entity Graph).** *An* entity graph *is a tuple $G = (N, E, \rho, \lambda, \tau, \sigma)$ were:*

1. *$N$ is a finite set of nodes representing entities in Bitcoin*
2. *$E$ is a finite set of edges representing transactions between Bitcoin entities*
3. *$\rho$ is a function that associates an edge $E$ with a pair of nodes in $N$*
4. *$\lambda : N \rightarrow SET^{+}(A)$ is a function that associates a node with a set of addresses from $A$ (i.e., $\lambda$ returns the addresses that are somehow controlled by a certain Bitcoin entity)*
5. *$\sigma : N \rightarrow SET^{+}(C)$ is a function that associates a node with a set of categories from $C$. Note that a node can carry several categories (e.g., exchange AND wallet provider)*
6. *$\tau : E \rightarrow SET^{+}(T)$ is a function that associates an edge with the set of transactions from $T$, which have taken place between two entities.*

Given two nodes $n_1, n_2 \in N$ and an edge $e \in E$ such that $\rho(e) = (n_1, n_2)$, we say that $n_1$ and $n_2$ are the *source entity* and the *target entity* of $e$ respectively. Further, we denote $T_{n_1,n_2} \in T$ as the set of transactions that transferred value from a source to a target entity, such that $\tau(e) = T_{n_1,n_2}$.
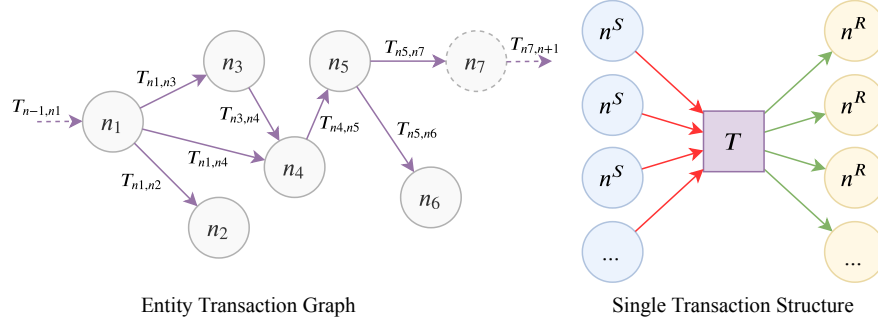


Entity Transaction Graph          Single Transaction Structure

**Fig. 1.** Simplified illustrations of an Entity Transaction Graph (left) and the related raw data structure (right) for a simple transaction in the graph, sending entities $n^S$ denoted as input with a *negative* amount, receiving entities $n^R$ denoted as output with a *positive* amount.

### 3.3  Identifying Selling Transactions

Given the directed nature of the entity graph, an entity can be the sender $(n^S)$ or recipient $(n^R)$ of transactions. Additionally, some entities in the graph can be

identified as being cryptocurrency exchanges $n_x$ such that $\sigma(n_x) = \{Exchange\}$. Therefore, we denote $n_x^S$ and $n_x^R$ as being sending and receiving exchanges, respectively. Figure 2 depicts all relevant subsets required for identifying selling transactions.
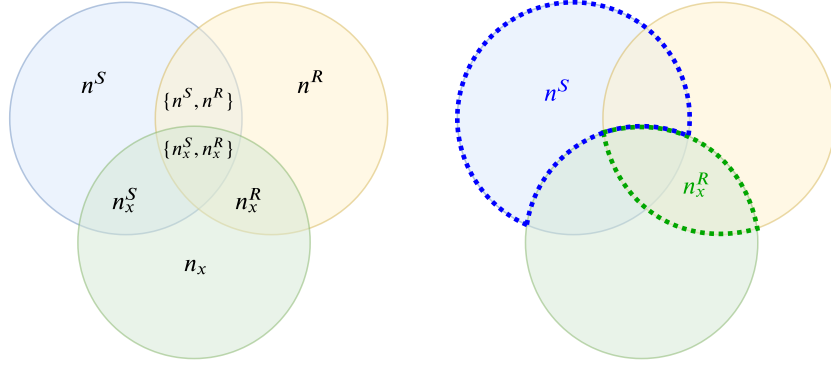


**Fig. 2.** The overall set (left) and the relevant subsets for sending non-exchange $n^S$ and receiving exchange $n_x^R$ entities outlined with dotted lines (right).

In practice, entities in the entity graph correspond to user wallets or software services that control private keys on behalf of their users. There are two types of wallets, (i) non-custodial also known as cold or offline wallets and (ii) custodial, hot or online wallets which are offered by wallet providers [22, p. 8]. Both types implicate differences in convenience, ease-of-use, and security [24]. Non-custodial wallets are decentralised, the investor owns its private key to access the wallet and has full control but also full responsibility over the funds. This means if the private key or the restore password gets irrecoverably lost, it is impossible to access the wallets funds.

Custodial wallets are often integrated in exchange platforms and function similarly to a bank account that stores fiat currency and one or more cryptocurrencies. A potential investor can initiate a cryptocurrency transfer to another custodial or non-custodial wallet as well as initiate a buy or sell transaction on the platform, similarly when exchanging one fiat currency to another. The custodian usually keeps the customer's private keys and also provides backup and accessibility measures for their customers [22, p. 13].

Under the assumption that an informed investor holds his cryptocurrency funds in some non-custodial wallet (e.g., a cold wallet), selling cryptocurrency units typically involves several steps: first, he creates a custodial wallet at some cryptocurrency exchange; second, he transfers funds from his non-custodial wallet to his exchange wallet; and third, he issues a sell order, which is then executed

by the exchange and typically involves the transfer of funds to another custodial wallet, which is assigned to another user, but controlled by the same exchange.

We are well-aware that this assumption doesn't hold for investors who incorrectly trust the safe custody of their assets in cryptocurrency exchanges and keep them in custodial wallets [8]. In this case, a sell order changes the balances in the exchange-controlled ledger but does not leave a footprint on the blockchain. Since custodial exchanges are black-boxes, it is currently not possible to reliably assess the extent of such exchange-internal "off-chain" transactions [3]. Nevertheless, since the aim of our work is to measure trading behaviour under specific market trends rather than to quantify overall trading volumes, we assume that we can safely base our further analysis on this assumption.
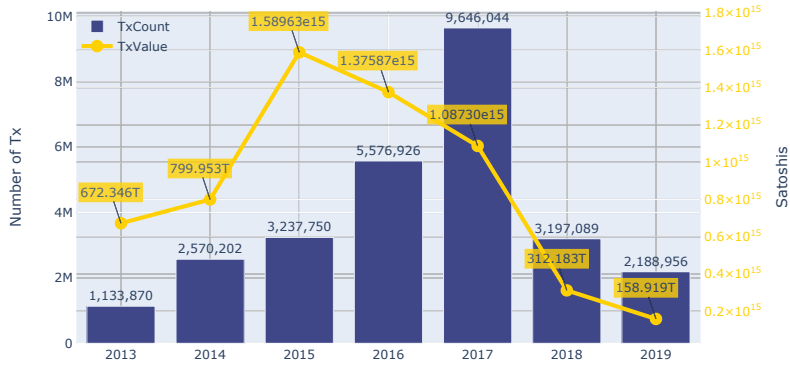


**Fig. 3.** Per-year view of the number of sell transactions (TxCount) and the related amount (TxValue) covered by the identified sell transactions.

Therefore, in order to measure the selling activities of an investor, we are interested in the second step within the above-mentioned process: the transfer of funds from a non-exchange-controlled wallet to exchange controlled wallets. Hence, we also exclude exchange-to-exchange transactions. More formally, we identify selling transactions by filtering those that have non-exchanges $(n^S)$ as source and exchanges as target $(n^R_x)$. This specific subset of selling transactions $t_s \subseteq T$ is of main interest in our further analysis. Figure 3 represents a high-level, aggregated yearly view of the number of selling transactions and the according transferred values of those transactions. We can clearly see a steep drop in the

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[8] Hacks on cryptocurrencies and other custodial wallet providers have become a major attack vector, with damages exceeding billions of dollar a year [2]

number of transactions and the amount of coins (Satoshis) transferred from 2017 to 2018 and 2019 consecutively. The reason for this is related to the drastic Bitcoin price drop in December 2017 when the price bubble did finally burst, highlighted later in Figure 4 in the data series *BTC price*. This event also led to a drop in the interest by the broader public and investors too, represented by the decrease of the overall sell transaction counts as well as transferred values.

### 3.4   Calculating Gains Realised (GR) and Losses Realised (LR)

To distinguish if a selling activity should be counted as a gain realised GR or as loss realised LR, we correlate each selling transaction $t_s$ with the market sentiment of the day it has been executed. We define the reference point for this decision as $\bar{\psi}$ for each technical indicator. For the Odean indicator this means the average of the opening and closing price of the asset on this day. For the technical indicators established buy and sell rules for $\bar{\psi}$ are applied, e.g. MACD buy (GR) for values greater zero, sell (LR) for below zero, similar for RSI buy (GR) for values greater or equal 50 and sell (LR) for values below 50. See appendix Table 4 for the complete rule set similar to a previous study by Gerritsen et al. [27].

To classify the market sentiment into either upward or downward-facing sentiment, the OHLC (open/high/low/close) data for the Bitcoin market with hourly resolution was acquired from the data broker Kaiko [9] via CSV files provided for multiple exchanges, covering the period as early as July 2010 to June 2020. Similarly like Bitcoinaverage [10] we calculated an exchange-independent global average price accross all exchanges. Such averaged prices are also used in other empirical research [65,60].

In order to classify Bitcoin selling activities either as GR or LR, we process and refine our dataset as follows:

1. OHLC (open, high, low, close) data from Kaiko is joined with the transactions $t_s$ that resulted out of the previous filtering steps
2. For each transaction, we compute $\bar{\psi}$ as the average price (Odean indicator) by averaging the opening and closing price of that hour or $\bar{\psi}$ being the respective reference point for a buy / sell decision for the specific technical indicators
3. For the Odean indicator the market of that day is labeled as either having a *positive* sentiment when the reference point $\bar{\psi}$ is *above* the open price $\psi$ ($\bar{\psi} > \psi$) and *negative* if the average price is *below* the open price $\psi$ ($\bar{\psi} < \psi$)
4. For the technical indicators the market of that day is labeled as either having a *positive* sentiment when the reference point $\bar{\psi}$ indicates a *buy* signal being categorised as GR or having a *negative* sentiment, indicating a *sell* signal being categorised as LR
5. All sell transactions $t_s$ from all identified entities are categorised as either gains realised GR ($t_s^{UP}$) due to positive sentiment, or losses realised LR

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[9] Kaiko.com - `https://www.kaiko.com/pages/historical-data`

[10] Bitcoinaverage.com - `https://bitcoinaverage.com/`

$(t_s^{DOWN})$ due to negative sentiment and counted per category and per indicator, such that $t_s = t_s^{UP} \cup t_s^{DOWN}$.

6. Finally, for each receiving exchange entity $n \in n_x^R$ within a certain time interval, we count transactions $t_s^{UP}$ with gains realised $(\bar{\psi} > \psi)$ and $t_s^{DOWN}$ with losses realised $(\bar{\psi} < \psi)$ and sum up the resulting values per indicator.

We implemented our computational method using Python [11] and published the method on a Github repository [12].

## 4  Analysis and Results

After having described our method in the last section, we now concentrate on answering our guiding research question, which is: *Do investors in cryptocurrencies like Bitcoin display a tendency to hold on to losing positions for far too long and sell out their winning positions too soon?* If this is the case, the disposition effect is also prevalent in cryptocurrency markets and we can infer that Bitcoin traders act irrationally.



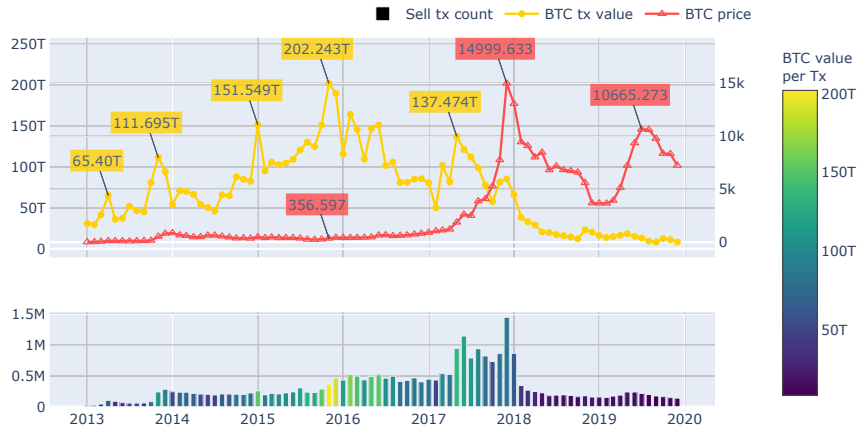**Fig. 4.** A combined plot of the monthly aggregated amount of Bitcoins (value in Satoshis) and number of sell transactions over the time period 2013 to 2019. The bar color coding represent the amount of Satoshis transferred in that month to link the sell transactions with the amount sold.

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[11] Python Programming Language - `https://www.python.org/`
[12] Github Repo - `https://github.com/jschatzmann/CryptoDisposition`

Before going into the details of our hypothesis test, we explore, in Figure 4, how Bitcoin sell transactions evolved over time in relation to the Bitcoin price. We can observe that before the general Bitcoin publicity-boom was starting in 2016 and taking off in 2017, the sold amount of Satoshis peaked in November 2015 with 202.243T at a BTC average price of 356.6 USD, the amount was transferred in a total number of 365.89k sell transactions indicated by the yellow bar plot in the second row. In the main boom year 2017 the transaction count significantly increased right to the end of December 2017 peaking at 1.4M transactions and 85.459T Satoshis transferred at a price point of 14.9k USD, flattening out significantly in January 2018 indicating decrease of investors interests and a tendency to withdraw after the price decline.

We will now investigate these observations in more detail: as a starting point, in Section 4.1, we explore computed gains realised (GR) and losses realised (LR) and investigate the relations between and distributions of these values. Then, in Section 4.2, we present the results of our hypothesis tests and illustrate how the disposition effect evolved over time in Section 4.3.

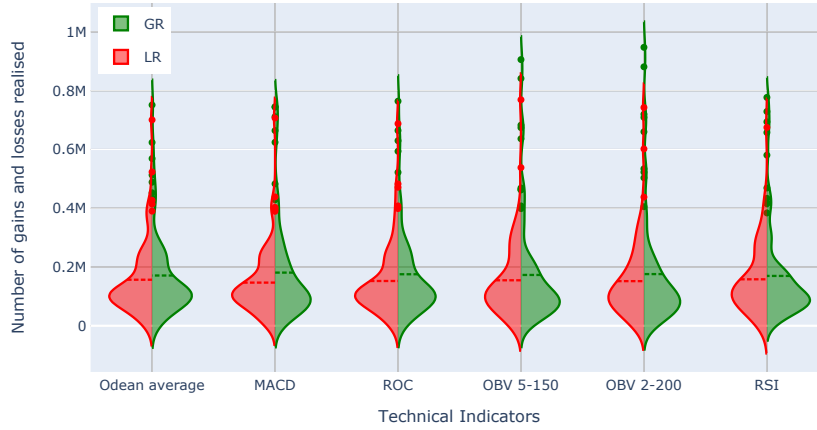## 4.1 Exploring Realised Gains and Losses



**Fig. 5.** Violin plots of GR and LR for the Odean average, MACD, ROC, OBV5-150, OBV2-200, and RSI, all GR mean values are above the LR mean values.

We computed gains realised (GR) and losses realised (LR) for each indicator and for each entity that can be mapped to a cryptocurrency exchange within

the Bitcoin ecosystem. In Figure 5, we compare the counts of LR and GR for the first six selected indicators, including the original Odean indicator based on the comparison of the closing price with the the average (hourly) price. We can observe that the mean values of GR lie above the mean values of LR for all technical indicators, providing the basis for the $t$-test.
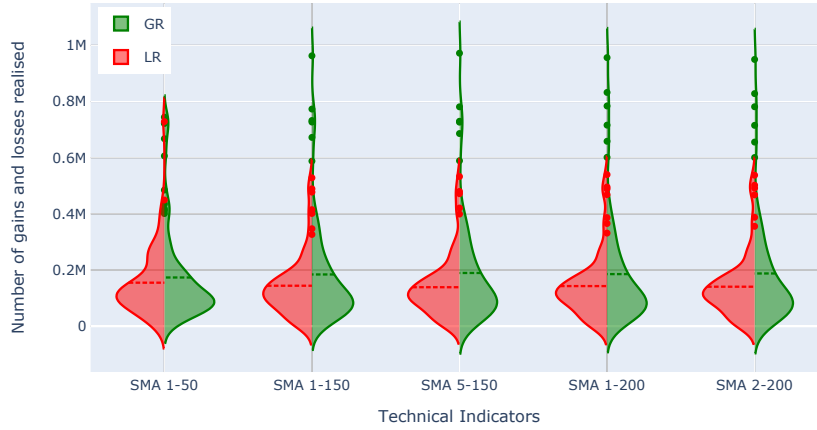


**Fig. 6.** Violin plots for the SMA indicators, the GR mean values are all above the LR mean values.

Similarly, all Simple Moving Average (SMA) indicators (see Appendix 6) represented in Figure 6 over the defined time window 2013 to 2019 also show that the GR mean values are above LR mean values. The results of the statistical significance tests, hence indicating disposition effect biased trading, will be discussed next.

### 4.2 Testing for the Disposition Effect in Bitcoin

Our empirical result for the Bitcoin market supports the existence of the disposition effect with an overall $t$-statistic of -7,8345 for the Odean average, as well as for most of the other technical indicators with exception of all TRB, OBV1-50, OBV1-150, OBV1-200, and BB that have all an opposite, positive $t$-statistic. The dataset covers all the years from 2013 to 2019. Hence, for the indicators Odean, MACD, ROC, all SMAs, OBV5-150, OBV2-200, and RSI, the $H_0$ can be *rejected* with a highly significant $p$-value of <0,001. For all TRBs, OBV1-50, OBV1-150, OBV2-200, and BB $H_0$ *cannot* be rejected.

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We based the measurement method on the model of T. Odean [48] and introduced the necessary adaptations to fit the remaining indicators and a portfolio of only one asset (in this case Bitcoin) and the specific market conditions impacted by the high volatility compared to established markets. Table 1 summarises the results of our analysis aggregated on a yearly basis for all indicators in scope.

**Table 1.** Overview of the $t$-statistic, the number of gains (GR) and losses (LR) realised based on the chosen indicator.

| Indicator | GR | LR | tstat | pval |
|---|---|---|---|---|
| Odean average | 14.379.005 | 13.169.226 | -7,8345 | <0,001 |
| MACD | 15.204.973 | 12.345.864 | -18,5573 | <0,001 |
| ROC | 14.739.285 | 12.811.552 | -12,4930 | <0,001 |
| RSI | 14.255.666 | 13.295.171 | -6,2187 | <0,001 |
| SMA 1-50 | 14.553.516 | 12.997.321 | -10,0807 | <0,001 |
| SMA 1-150 | 15.462.935 | 12.087.902 | -21,9302 | <0,001 |
| SMA 5-150 | 15.905.976 | 11.644.861 | -27,7526 | <0,001 |
| SMA 1-200 | 15.568.209 | 11.982.628 | -23,3101 | <0,001 |
| SMA 2-200 | 15.756.912 | 11.793.925 | -25,7890 | <0,001 |
| TRB 50 | 10.557.364 | 16.993.473 | 42,2604 | <0,001 |
| TRB 150 | 10.980.287 | 16.570.550 | 36,5757 | <0,001 |
| TRB 200 | 11.176.217 | 16.374.620 | 33,9617 | <0,001 |
| OBV 1-50 | 4.105.669 | 23.445.168 | 145,1105 | <0,001 |
| OBV 1-150 | 4.088.526 | 23.462.311 | 145,4565 | <0,001 |
| OBV 5-150 | 14.535.322 | 13.015.515 | -9,8446 | <0,001 |
| OBV 1-200 | 4.081.926 | 23.468.911 | 145,5899 | <0,001 |
| OBV 2-200 | 14.784.221 | 12.766.616 | -13,0770 | <0,001 |
| BB | 981.188 | 1.782.147 | 15,7980 | <0,001 |

Table 1 shows the original Odean average value as well as MACD, ROC, RSI, all SMAs, and OBV5-150 including OBV2-200 with highly significant minus $t$-values. Those findings are in line with the original method of Terence Odean and his study utilising trading data of 10.000 accounts with 162.948 records [48, p. 1789].

A hypothesis for the non-minus overall $t$-statistic for trading range breakout (TRB) and Boellinger Bands (BB) could be that in the years 2013 to 2016 and even into early 2017 were stable, more linear price changes and no massive, explosive price movement took place. Hence range breakout strategies would not yield excessive gains. Indeed on the yearly view, all TRB indicators indicate statistical significant minus $t$-statistics for the boom and bust year 2017: TRB50 (-29,1843), TRB150 (-40,4239), and TRB200 (-44,9203) having even more extreme values than their SMA counterparts. Taking a closer monthly look into the year 2017 for BB, only four months (February, April, May, and November) are highly significant ($p$ <0,001) in the positive range. Only the year 2018 signals a statistical significant minus $t$-statistic of BB (-4,0693), assuming the risk averse

investors following a BB strategy tried to mitigate for the losses by selling the remaining and newly achieved gains more readily than in the years before. The detailed yearly view is available in the appendix in Table 2 and Table 3. The picture for OBV is ambivalent with three indicators in the plus and two in the minus range.

The main finding of the statistical tests is that the overall results covering the complete time frame from 2013 to 2019 provide significant evidence for the prevalence of the disposition effect. Out of 18 total indicators, 11 show clear evidence for the existence of the disposition effect in the Bitcoin market, including the main Odean average indicator.

### 4.3   Longitudinal Analysis

In Figure 7, we show the evolution of $t$-statistics over time for selected indicators (Odean, RSI, and ROC) on a monthly basis. A complete yearly result is available in Table 2 and Table 3 in the Appendix as well as more detailed listing on the monthly and per indicator view is provided in the Github repository [13]. When examining individual months, we can observe significant differences in the $t$-statistic: there are time periods where the negative $t$-values indicate strong disposition effect impacted trading (e.g. early 2017 where even TRB indicators signal gains realised) and periods with positive $t$-values supposedly rational trading (e.g. almost the entire years 2014, 2015, and 2016). The $p$-value heatmap for the three selected indicators in the second row indicates with dark green highly significant $p$-values ($<0.001$) up to white for significant ($<0.05$) values. A combination of the heatmap and the line plot data signals significant disposition effect driven trading (minus $t$-statistics) for all three selected indicators. This is true for almost the entire year 2017, changing to a more ambiguous picture in 2018 with mixed signals over the months.

The heatmap in Figure 7 below indicates the $p$-values only for the relevant minus $t$-statistic given in the upper part of the plot. We see extreme $t$-values in the early years 2013 and 2014 with rather low sell transaction counts, low values and low price, as depicted earlier in Figure 4. Compared to this, in 2017 where price, sell transactions, and transferred values peaked, we see a almost constant level of significant $t$-values confirming the disposition effect throughout the whole year.

Looking at the overall longitudinal perspective, the data shows a major shift in 2017 of the Bitcoin ecosystem from an expert / niche market to a broader user base driven market, assumed due to the increased public recognition and media coverage. This lead to a drastic increase in the number of sell transaction and the related higher transfer values. Since this turning point in early 2017, most technical indicators signal continuing, stronger disposition effect biased selling activities by the investors.

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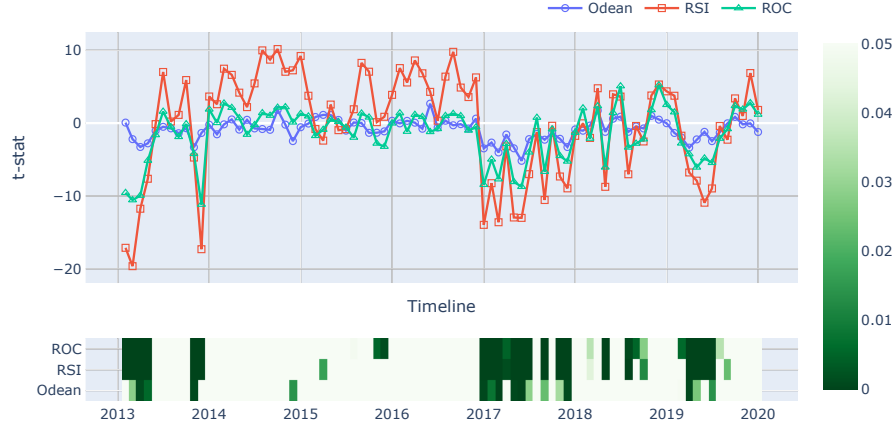[13] CryptoDisposition - `https://github.com/jschatzmann/CryptoDisposition`

**Fig. 7.** Plot of *t*-statistics for Odean, RSI, and ROC GR and LR in a monthly view from Jan-2013 to Dec-2019.

## 5 Discussion

Following the presented empirical results in the previous section, we now continue to discuss and interpret the key findings of our study and point out the known limitation and possible future directions.

### 5.1 Key findings

Our key finding confirms that the disposition effect is prevalent in the Bitcoin cryptocurrency market for the overall period from January 2013 to December 2019 for eleven out of eighteen indicators, when regarded on a yearly basis. When inspecting the evolution of the disposition effect on a monthly and indicator by indicator basis, we found a more ambiguous situation where the differences of the means are heavily allocated either on the one or the other side of the LR/GR spectrum.

The disposition effect is not consistently prevalent over several months but indeed switches drastically from significantly negative to positive and vice versa (e.g. see Figure 7 early years 2013 till 2016 with only limited exceptions, indicating significant more losses realised, compared to the whole year 2017 confirming the presence of the disposition effect). The reason for this is yet unclear and would be subject to future research.

Although Bitcoin experiences unusual high volatility, the market itself seems to be controlled by informed investors as found by Baur and Dimpfl [7] and the

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timing of the sell activities combined with positive or negative shocks would need a closer look. Also, the months from January 2017 till December 2017 depicted in Table 3 where fourteen of the indicators signal strong disposition effect impacted trading attract attention. A speculative reason could be that Bitcoin gained a lot of traction in the media, correlating with a steep price increase for the entire year 2017 before coming to an abrupt halt and decline early 2018, potentially inspiring more non-professional traders to enter the market.

### 5.2   Limitations

Currently, we quantify the selling activities of clusters by counting sells in different market conditions without considering the amounts of Bitcoins sold. Hence we don't assess the economic impact of a transaction on the investor's bottom line but only the sell activity itself. Despite being a limitation, this is still in line with the approach of Odean [48], who also focused on the number of transactions only. The main difference to his approach is that he compared the proportion of gains realised (PGR) and the proportion of losses realised (PLR) based on an investor's portfolio. Due to the high volatility of Bitcoin and as only one asset was considered, this classification approach yielded no suitable results as the spread of highs and lows was too large and stretched over the average purchase price line, providing no indication of the market situation. Hence, we used the hourly average price $\bar{\psi}$ of open and close price for the Odean indicator and in the literature established *buy (GR)* or *sell (LR)* rules for the technical indicators described in Section 3.4.

Another limitation, which we already pointed out in Section 3.3, is that many (uninformed) Bitcoin users nowadays use custodial wallets, which are provided and de-facto controlled by exchanges, instead of running their own clients. As a consequence, many trades are executed "off-chain" within the shadows of black-box services. Since such transactions are not represented on the blockchain, we cannot identify them via our current approach and they are currently not considered in our analysis. However, our work presently captures informed traders who transfer their funds to an exchange before executing a sell transaction.

Finally, our work is limited by the unknown reliability of the Bitcoin co-spend clustering heuristics [40]. Even though this technique has become an integral method in cryptoasset analytics and forensics, it is still not possible to quantify its reliability because ground-truth datasets are still missing.

### 5.3   Future work

Our research covered the still most important cryptocurrency Bitcoin but ignores other altcoins playing an important role in the crypto-economy as well. Hence, our current measurement method and analytics tool-set are easily applicable for other cryptocurrencies that follow the *Unspent Transaction Output (UTXO)* model such as Bitcoin Cash, LiteCoin or Zcash. Furthermore, a detailed investigation of the yearly variation summarised in Table 2 and 3 as well as the

monthly fluctuations available on Github [14] and their influencing factors are of interest as they are currently unknown.

The available data allows for very specific, micro-segmented timeframes allowing an investigation of the selling and buying behaviour in those trading windows with a much higher resolution. The hourly moving time window chosen for this research for the applied indicators yielded further insights compared to the average daily view of the market sentiment. Nevertheless, further analysis in the relationship between the technical indicators itself and potential correlations as well as a weighted indicator combining the transaction with the amount of Bitcoins sold would be of interest.

Attributing addresses or entities that are involved in trades would certainly contribute to a better overall understanding of the factors influencing the evolution of LR and GR. However, collecting so-called *attribution tags* is a resource-intensive data collection process, which is usually implemented by commercial tool providers.

An alternative approach could take multiple technical indicators into account when evaluating the investors' behaviour described via multiple regression. Market momentum, market trend, and market volatility defined by well-known technical indicators influencing investors' behaviour defined via the transaction amount sold and transaction count. Such a model could add an additional viewpoint and augment the established GR and LR model used for this research.

## 6   Conclusions

In our work we empirically validated the prevalence of the disposition effect in Bitcoin. Since cryptocurrency markets can still be viewed as being atypical markets lacking central authorities and regulation and exhibiting strong volatility, we showed its prevalence also in such markets. Our results show that this effect manifest itself significantly from the boom and bust year 2017 onwards, where Bitcoin attracted more investors due to increased publicity, leading also to a significant increase in trading activities. This continuing trend of disposition effect biased trading continues up to the end of 2019 of our analysis cut-off window. From the prevalence of the disposition effect in Bitcoin, we can conclude that cryptocurrency traders act just as irrationally as traders in traditional markets.

Our work also complements a long line of research in the field of behavioral finance, closing an open gap by confirming the existence of a known economic phenomenon in the still most important cryptocurrency market. In addition, we proposed a calculation method to quantify the disposition effect, which is tailored to the specific characteristics of cryptocurrency transactions and can easily be used for analysing transactions in other markets, if they follow the same transaction model.

In our future work, we will concentrate on solving the previously discussed open issues and limitations and expand our analysis to additional cryptocurrency

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[14] Github Repo - `https://github.com/jschatzmann/CryptoDisposition`

markets. We will also investigate how our methods can be extended for the analysis of more general cryptoasset markets, which support trading of arbitrary tokens.

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## References

1. Achelis, S.B.: Technical Analysis from A to Z-Achelis Steven .pdf. Vision Books (2003)
2. Anderson, R., Barton, C., Bölme, R., Clayton, R., Ganán, C., Grasso, T., Levi, M., Moore, T., Vasek, M.: Measuring the changing cost of cybercrime. In: The 2019 Workshop on the Economics of Information Security (2019)
3. Anderson, R., Shumailov, I., Rietmann, A., Ahmed, M.: Bitcoin Redux (2018)
4. Barber, B., Odean, T.: Individual Investors. In: Thaler, R.H. (ed.) Advances in Behavioral Finance, Volume II, chap. 15, pp. 543–569. Princeton University Press, Princeton (2005)
5. Barberis, N.C.: Thirty Years of Prospect Theory in Economics: A Review and Assessment. Journal of Economic Perspectives **27**(1), 173–196 (feb 2013). https://doi.org/10.1257/jep.27.1.173, `10.1257/jep.27.1.173`.
6. Bartos, J.: Does Bitcoin follow the hypothesis of efficient market? International Journal of Economic Sciences **IV**(No. 2), pp. 10–23 (2015). https://doi.org/10.20472/ES.2015.4.2.002
7. Baur, D.G., Dimpfl, T.: Asymmetric volatility in cryptocurrencies. Economics Letters **173**, 148–151 (dec 2018). https://doi.org/10.1016/j.econlet.2018.10.008, `https://www.sciencedirect.com/science/article/pii/S016517651830421Xhttps://linkinghub.elsevier.com/retrieve/pii/S016517651830421X`
8. Baur, D.G., Lee, A.D., Hong, K.: Bitcoin: Currency or Investment? SSRN Electronic Journal (February), 1–21 (2015). https://doi.org/10.2139/ssrn.2561183, `http://www.ssrn.com/abstract=2561183`
9. Bruce, B.: Handbook of Behavioral Finance. Edward Elgar Publishing (2010). https://doi.org/10.4337/9781849809108, `http://www.elgaronline.com/view/9781848446519.xml`
10. Budish, E.B.: The Economic Limits of Bitcoin and the Blockchain. SSRN Electronic Journal (2018). https://doi.org/10.2139/ssrn.3197300, `https://www.ssrn.com/abstract=3197300`
11. Buterin, V.: A next-generation smart contract and decentralized application platform. Etherum (January), 1–36 (2014), `http://buyxpr.com/build/pdfs/EthereumWhitePaper.pdf`
12. Caginalp, G., Balenovich, D.: A theoretical foundation for technical analysis. Journal of Technical Analysis **59**(1998), 5–21 (2003)
13. Chu, J., Nadarajah, S., Chan, S.: Statistical analysis of the exchange rate of bitcoin. PLoS ONE **10**(7), 1–27 (2015). https://doi.org/10.1371/journal.pone.0133678

14. Chuen, D.L.K.: Handbook of Digital Currency. Elsevier (2015). https://doi.org/10.1016/C2014-0-01905-3, `https://linkinghub.elsevier.com/retrieve/pii/C20140019053`

15. Ciaian, P., Rajcaniova, M., Kancs, D.: The digital agenda of virtual currencies: Can BitCoin become a global currency? Information Systems and e-Business Management **14**(4), 883–919 (nov 2016). https://doi.org/10.1007/s10257-016-0304-0, `http://link.springer.com/10.1007/s10257-016-0304-0`

16. Clark, E., Qiao, Z., Wong, W.K.: Theories of risk: Testing investor behavior on the taiwan stock and stock index futures markets. Economic Inquiry **54**(2), 907–924 (2016). https://doi.org/10.1111/ecin.12288

17. Coval, J.D., Shumway, T.: Do Behavioral Biases Affect Prices? The Journal of Finance **60**(1), 1–34 (feb 2005). https://doi.org/10.1111/j.1540-6261.2005.00723.x, `http://doi.wiley.com/10.1111/j.1540-6261.2005.00723.x`

18. Daly, K.: Efficiently Inefficient: How Smart Money Invests and Market Prices Are Determined, by Lasse Heje Pedersen (Princeton University Press, Princeton, NJ, 2015), pp. 348. Economic Record **93**(300), 176–177 (mar 2017). https://doi.org/10.1111/1475-4932.12321, `http://doi.wiley.com/10.1111/1475-4932.12321`

19. Di Francesco Maesa, D., Marino, A., Ricci, L.: Detecting artificial behaviours in the Bitcoin users graph. Online Social Networks and Media **3-4**, 63–74 (oct 2017). https://doi.org/10.1016/j.osnem.2017.10.006

20. Doguet, J.: The nature of the form: Legal and regulatory issues surrounding the bitcoin digital currency system (2013)

21. European Banking Authority: EBA Opinion on 'virtual currencies' (2016)

22. European Central Bank: Virtual currency schemes - a further analysis. ECB publication (QB-04-15-134-EN-N) (2015), `https://www.ecb.europa.eu/pub/pdf/other/virtualcurrencyschemesen.pdf`

23. Ford, B., Böhme, R.: Rationality is Self-Defeating in Permissionless Systems pp. 1–10 (oct 2019), `http://arxiv.org/abs/1910.08820`

24. Frantz, C.K., Nowostawski, M.: Banking Beyond Banks and Money. New Economic Windows, Springer International Publishing, Cham (2016). https://doi.org/10.1007/978-3-319-42448-4, `http://link.springer.com/10.1007/978-3-319-42448-4`

25. Frazzini, A.: The Disposition Effect and Under-reaction to News (2004), `http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.196.9338{&}rep=rep1{&}type=pdf`

26. Genesove, D., Mayer, C.: Loss Aversion and Seller Behavior: Evidence from the Housing Market. The Quarterly Journal of Economics **116**(4), 1233–1260 (nov 2001). https://doi.org/10.1162/003355301753265561, `https://academic.oup.com/qje/article-lookup/doi/10.1162/003355301753265561`

27. Gerritsen, D.F., Bouri, E., Ramezanifar, E., Roubaud, D.: The profitability of technical trading rules in the Bitcoin market. Finance Research Letters (July), 1–10 (aug 2019). https://doi.org/10.1016/j.frl.2019.08.011, `https://doi.org/10.1016/j.frl.2019.08.011https://linkinghub.elsevier.com/retrieve/pii/S1544612319303770`

28. Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M.C., Siering, M.: Bitcoin - Asset or Currency? Revealing Users' Hidden Intentions. In: Twenty Second European Conference on Information Systems. p. 14. Tel Aviv (2014)

29. Grinblatt, M., Keloharju, M.: What Makes Investors Trade? The Journal of Finance **56**(2), 589–616 (apr 2001). https://doi.org/10.1111/0022-1082.00338, `http://doi.wiley.com/10.1111/0022-1082.00338`

30. Gudgeon, L., Moreno-Sanchez, P., Roos, S., McCorry, P., Gervais, A.: Sok: Off the chain transactions. In: Finanical Cryptography and Data Security 2020 (2019)
31. Haslhofer, B., Karl, R., Filtz, E.: O Bitcoin where art thou? Insight into large-scale transaction graphs. In: CEUR Workshop Proceedings (2016)
32. Henry, C.S., Huynh, K.P., Nicholls, G., Nicholson, M.W.: 2018 Bitcoin Omnibus Survey: Awareness and Usage. Tech. rep., Bank of Canada, Ottawa (2019)
33. Hileman, G., Rauchs, M.: 2017 Global Cryptocurrency Benchmarking Study. SSRN Electronic Journal (2017). https://doi.org/10.2139/ssrn.2965436, `https://www.jbs.cam.ac.uk/fileadmin/user{_}upload/research/centres/alternative-finance/downloads/2017-global-cryptocurrency-benchmarking-study.pdfhttp://www.ssrn.com/abstract=2965436`
34. Kahneman, D., Tversky, A.: Prospect Theory: An Analysis of Decision under Risk. Econometrica **47**(2), 263–291 (1979)
35. Kalodner, H., Goldfeder, S., Chator, A., Möser, M., Narayanan, A.: BlockSci: Design and applications of a blockchain analysis platform (sep 2017), `http://arxiv.org/abs/1709.02489`
36. Kaustia, M.: Disposition Effect. In: Behavioral Finance, pp. 169–189. John Wiley & Sons, Inc., Hoboken, NJ, USA (nov 2011). https://doi.org/10.1002/9781118258415.ch10, `http://doi.wiley.com/10.1002/9781118258415.ch10`
37. Kirkpatrick, C.D., Dahlquist, J.R.: Technical Analysis: The Complete Resource for Financial Market Technicians. Pearson Education Inc., New Jersey (2007)
38. Malone, D., O'Dwyer, K.: Bitcoin Mining and its Energy Footprint. In: 25th IET Irish Signals & Systems Conference 2014 and 2014 China-Ireland International Conference on Information and Communities Technologies (ISSC 2014/CIICT 2014). pp. 280–285. Institution of Engineering and Technology (2014). https://doi.org/10.1049/cp.2014.0699, `http://digital-library.theiet.org/content/conferences/10.1049/cp.2014.0699`
39. Meiklejohn, S., Pomarole, M., Jordan, G., Levchenko, K., McCoy, D., Voelker, G.M., Savage, S.: A Fistful of Bitcoins: Characterizing payments among men with no names. Proceedings of the Internet Measurement Conference - IMC '13 (6), 127–140 (2013). https://doi.org/10.1145/2504730.2504747, `http://dl.acm.org/citation.cfm?id=2504730.2504747`
40. Meiklejohn, S., Pomarole, M., Jordan, G., Levchenko, K., McCoy, D., Voelker, G.M., Savage, S.: A fistful of Bitcoins. Communications of the ACM **59**(4), 86–93 (mar 2016). https://doi.org/10.1145/2896384, `http://dl.acm.org/citation.cfm?doid=2907055.2896384`
41. Metzger, M.A.: Biases in Betting: An Application of Laboratory Findings. Psychological Reports **56**(3), 883–888 (jun 1985). https://doi.org/10.2466/pr0.1985.56.3.883, `http://journals.sagepub.com/doi/10.2466/pr0.1985.56.3.883`
42. Möser, M., Böhme, R.: Trends, Tips, Tolls: A Longitudinal Study of Bitcoin Transaction Fees. In: Financial Cryptography and Data Security, pp. 19–33. Springer Berlin Heidelberg, Berlin, Heidelberg, fc 2015 in edn. (2015). https://doi.org/10.1007/978-3-662-48051-9 2
43. Möser, M., Böhme, R.: The price of anonymity: empirical evidence from a market for Bitcoin anonymization. Journal of Cybersecurity **3**(2), 127–135 (jun 2017). https://doi.org/10.1093/cybsec/tyx007, `https://academic.oup.com/cybersecurity/article/3/2/127/4057584`

44. Mullan, P.C.: The Digital Currency Challenge - Shaping Online Payment Systems through US Financial Regulations. Palgrave Macmillan, New York City, first edit edn. (2014). https://doi.org/10.1057/9781137382559.0001

45. Murphy, J.J.: Technical Analysis of the Financial Markets: A Comprehensive Guide to Trading Methods and Applications. New York Institute of Finance, New York (1999)

46. Nakamoto, S.: Bitcoin: A Peer-to-Peer Electronic Cash System. Bitcoin Publishing (2008), www.bitcoin.org

47. Ober, M., Katzenbeisser, S., Hamacher, K.: Structure and Anonymity of the Bitcoin Transaction Graph. Future Internet **5**(2), 237–250 (may 2013). https://doi.org/10.3390/fi5020237, http://www.mdpi.com/1999-5903/5/2/237/

48. Odean, T.: Are Investors Reluctant to Realize Their Losses? The Journal of Finance **53**(5), 1775–1798 (oct 1998). https://doi.org/10.1111/0022-1082.00072, http://doi.wiley.com/10.1111/0022-1082.00072

49. Pring, M.J.: Study Guide for Technical Analysis Explained. McGraw-Hill, 5 edn. (2014)

50. Ranshous, S., Joslyn, C.A., Kreyling, S., Nowak, K., Samatova, N.F., West, C.L., Winters, S.: Exchange pattern mining in the bitcoin transaction directed hypergraph. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). vol. 10323 LNCS, pp. 248–263 (2017)

51. Reid, F., Harrigan, M.: An analysis of anonymity in the bitcoin system pp. 1318–1326 (jan 2013), https://arxiv.org/abs/1107.4524

52. Rodriguez, M.A., Neubauer, P.: Constructions from dots and lines. Bulletin of the American Society for Information Science and Technology **36**(6), 35–41 (2010)

53. Ron, D., Shamir, A.: Quantitative Analysis of the Full Bitcoin Transaction Graph (2012), https://eprint.iacr.org/2012/584.pdf

54. Roubini, N.: The Great Crypto Heist (2019), https://www.project-syndicate.org/commentary/cryptocurrency-exchanges-are-financial-scams-by-nouriel-roubini-2019-07?barrier=accesspaylog

55. Schuster, E.P.: Cloud Crypto Land. SSRN Electronic Journal (2018). https://doi.org/10.2139/ssrn.3476678, https://ssrn.com/abstract=3476678https://www.ssrn.com/abstract=3476678

56. Shapira, Z., Venezia, I.: Patterns of behavior of professionally managed and independent investors. Journal of Banking & Finance **25**(8), 1573–1587 (aug 2001). https://doi.org/10.1016/S0378-4266(00)00139-4, http://linkinghub.elsevier.com/retrieve/pii/S0378426600001394

57. Shefrin, H.: Beyond greed and fear : understanding behavioral finance and the psychology of investing. Oxford University Press, New York, 1 edn. (2007)

58. Shefrin, H., Statman, M.: The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence. The Journal of Finance **40**(3), 777–790 (jul 1985). https://doi.org/10.2307/2327802, http://www.jstor.org/stable/2327802?origin=crossref

59. Shumway, T., Wu, G.: Does Disposition Drive Momentum? SSRN Electronic Journal (May), 713–743 (2005). https://doi.org/10.2139/ssrn.686901, http://www.ssrn.com/abstract=686901

60. Spenkelink, H.: The Adoption Process of Cryptocurrencies - Identifying factors that influence the adoption of cryptocurrencies from a multiple stakeholder perspective. Ph.D. thesis (2014), http://essay.utwente.nl/65677/

61. Stoll, C., Klaaßen, L., Gallersdörfer, U.: The Carbon Footprint of Bitcoin. Joule **3**(7), 1647–1661 (jul 2019). https://doi.org/10.1016/j.joule.2019.05.012
62. Tang, D.: Why People Won't Buy Your Product Even Though It's Awesome. Flevy Blog pp. 1–7 (2013), `http://flevy.com/blog/why-people-wont-buy-your-product-even-though-its-awesome/`
63. The Economist: Crypto-correction: Bitcoin and its rivals offer no shelter from the storm. Economist (United Kingdom) **414**(9075), 1–5 (2018), `https://www.economist.com/finance-and-economics/2018/02/10/bitcoin-and-its-rivals-offer-no-shelter-from-the-storm`
64. Tu, K.V., Meredith, M.W.: Rethinking Virtual Currency Regulation in the Bitcoin Age. Washington Law Review (2015)
65. Urquhart, A.: The inefficiency of Bitcoin. Economics Letters **148**, 80–82 (nov 2016). https://doi.org/10.1016/j.econlet.2016.09.019, `https://linkinghub.elsevier.com/retrieve/pii/S0165176516303640`
66. Weber, M., Camerer, C.F.: The disposition effect in securities trading: an experimental analysis. Journal of Economic Behavior & Organization **33**(2), 167–184 (jan 1998). https://doi.org/10.1016/S0167-2681(97)00089-9, `http://linkinghub.elsevier.com/retrieve/pii/S0167268197000899`
67. White, L.H.: The Market for Cryptocurrencies (2014), `https://papers.ssrn.com/sol3/papers.cfm?abstract{_}id=2538290`
68. van Wijk, D.: What can be expected from the BitCoin. Ph.D. thesis (2013)
69. Yermack, D.: Is Bitcoin a Real Currency? An Economic Appraisal. In: Handbook of Digital Currency, pp. 31–43. Elsevier (2015). https://doi.org/10.1016/B978-0-12-802117-0.00002-3, `http://linkinghub.elsevier.com/retrieve/pii/B9780128021170000023`
70. Zuchel, H.: The disposition effect: Explanations, experimental evidence and implications for asset pricing. Dissertation, University of Mannheim (2002)

# Appendix

**Table 2.** Details of GR and LR on a per year basis 2013 to 2016

| Indicator | 2013 GR | 2013 LR | t-stat | pval | 2014 GR | 2014 LR | t-stat | pval | 2015 GR | 2015 LR | t-stat | pval | 2016 GR | 2016 LR | t-stat | pval | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Odean average | 596.405 | 537.363 | -3,3086 | <0,001 | 1.307.766 | 1.262.436 | -1,5615 | 0,1184 | 1.627.461 | 1.610.289 | -0,4373 | 0,6619 | 2.800.480 | 2.775.656 | -0,3858 | 0,6997 | 5.281.833 |
| MACD | 709.128 | 424.742 | -16,1624 | <0,001 | 1.095.080 | 1.475.122 | 13,2197 | <0,001 | 1.682.980 | 1.554.770 | -3,2672 | 0,0011 | 2.848.657 | 2.728.269 | -1,8712 | 0,0614 | 6.123.973 |
| ROC | 651.884 | 481.986 | -9,5644 | <0,001 | 1.233.911 | 1.336.291 | 3,5288 | <0,001 | 1.669.141 | 1.568.609 | -2,5613 | 0,0104 | 2.837.856 | 2.739.070 | -1,5353 | 0,1247 | 5.608.260 |
| RSI | 657.032 | 476.838 | -10,1506 | <0,001 | 963.319 | 1.606.883 | 22,8157 | <0,001 | 1.486.810 | 1.750.940 | 6,7443 | <0,001 | 2.309.126 | 3.267.800 | 15,0900 | <0,001 | 6.047.438 |
| SMA 1-50 | 682.677 | 451.193 | -13,0901 | <0,001 | 996.370 | 1.573.832 | 20,3546 | <0,001 | 1.571.642 | 1.666.108 | 2,4067 | 0,0161 | 2.453.708 | 3.123.218 | 10,4689 | <0,001 | 6.113.060 |
| SMA 1-150 | 767.555 | 366.315 | -23,1486 | <0,001 | 976.778 | 1.593.424 | 21,8084 | <0,001 | 1.716.471 | 1.521.279 | -4,9782 | <0,001 | 2.848.185 | 2.728.741 | -1,8565 | 0,0634 | 6.536.528 |
| SMA 5-150 | 784.487 | 349.383 | -25,2386 | <0,001 | 1.035.352 | 1.534.850 | 17,5025 | <0,001 | 1.822.321 | 1.415.429 | -10,4269 | <0,001 | 3.072.511 | 2.504.415 | -8,8676 | <0,001 | 6.572.778 |
| SMA 1-200 | 767.651 | 366.219 | -23,1603 | <0,001 | 950.463 | 1.619.739 | 23,7850 | <0,001 | 1.757.689 | 1.480.061 | -7,0909 | <0,001 | 2.910.618 | 2.666.308 | -3,7996 | <0,001 | 6.623.149 |
| SMA 2-200 | 771.299 | 362.571 | -23,6078 | <0,001 | 983.827 | 1.586.375 | 21,2836 | <0,001 | 1.804.674 | 1.433.076 | -9,5127 | <0,001 | 3.030.075 | 2.546.851 | -7,5335 | <0,001 | 6.607.762 |
| TRB 50 | 536.364 | 597.506 | 3,4264 | <0,001 | 217.171 | 2.353.031 | 119,0684 | <0,001 | 112.689 | 3.125.061 | 134,1248 | <0,001 | 337.293 | 5.239.633 | 131,1493 | <0,001 | 6.476.343 |
| TRB 150 | 650.317 | 483.553 | -9,3861 | <0,001 | 250.256 | 2.319.946 | 110,0700 | <0,001 | 70.408 | 3.167.342 | 146,7473 | <0,001 | 326.765 | 5.250.161 | 132,8402 | <0,001 | 7.024.919 |
| TRB 200 | 668.385 | 465.485 | -11,4477 | <0,001 | 261.247 | 2.308.955 | 107,3426 | <0,001 | 72.366 | 3.165.384 | 146,1080 | <0,001 | 323.832 | 5.253.094 | 133,3190 | <0,001 | 7.225.752 |
| OBV 1-50 | 0 | 1.133.870 | 86,4908 | <0,001 | 0 | 2.570.202 | 273,5955 | <0,001 | 0 | 3.237.750 | 174,7193 | <0,001 | 0 | 5.576.926 | 229,5636 | <0,001 | 0 |
| OBV 1-150 | 0 | 1.133.870 | 86,4908 | <0,001 | 0 | 2.570.202 | 273,5955 | <0,001 | 0 | 3.237.750 | 174,7193 | <0,001 | 0 | 5.576.926 | 229,5636 | <0,001 | 0 |
| OBV 5-150 | 652.038 | 481.832 | -9,5819 | <0,001 | 958.289 | 1.611.913 | 23,1941 | <0,001 | 1.857.794 | 1.379.956 | -12,2739 | <0,001 | 2.407.136 | 3.169.790 | 11,9477 | <0,001 | 6.339.800 |
| OBV 1-200 | 0 | 1.133.870 | 86,4908 | <0,001 | 0 | 2.570.202 | 273,5955 | <0,001 | 0 | 3.237.750 | 174,7193 | <0,001 | 0 | 5.576.926 | 229,5636 | <0,001 | 0 |
| OBV 2-200 | 653.054 | 480.816 | -9,6975 | <0,001 | 931.776 | 1.638.426 | 25,2069 | <0,001 | 1.883.104 | 1.354.646 | -13,6003 | <0,001 | 2.512.863 | 3.064.063 | 8,6016 | <0,001 | 6.602.609 |
| BB | 33.998 | 82.136 | 7,7367 | <0,001 | 19.150 | 141.810 | 17,5777 | <0,001 | 42.140 | 161.542 | 11,9940 | <0,001 | 39.547 | 345.814 | 18,6984 | <0,001 | 482.413 |

**Table 3.** Details of GR and LR on a per year basis 2017 to 2019

| Indicator | 2017 GR | 2017 LR | t-stat | pval | 2018 GR | 2018 LR | t-stat | pval | 2019 GR | 2019 LR | t-stat | pval |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Odean average | 5.281.833 | 4.362.497 | -7,7721 | <0,001 | 1.614.972 | 1.582.117 | -0,6935 | 0,4880 | 1.150.088 | 1.038.868 | -4,2275 | <0,001 |
| MACD | 6.123.973 | 3.522.071 | -22,5491 | <0,001 | 1.563.742 | 1.633.347 | 1,4693 | 0,1418 | 1.181.413 | 1.007.543 | -6,6187 | <0,001 |
| ROC | 5.608.260 | 4.037.784 | -13,3651 | <0,001 | 1.566.864 | 1.630.225 | 1,3375 | 0,1811 | 1.171.369 | 1.017.587 | -5,8508 | <0,001 |
| RSI | 6.047.438 | 3.598.606 | -21,1522 | <0,001 | 1.590.486 | 1.606.603 | 0,3402 | 0,7337 | 1.201.455 | 987.501 | -8,1551 | <0,001 |
| SMA 1-50 | 6.113.060 | 3.532.984 | -22,3490 | <0,001 | 1.552.832 | 1.644.257 | 1,9301 | 0,0536 | 1.183.227 | 1.005.729 | -6,7575 | <0,001 |
| SMA 1-150 | 6.536.528 | 3.109.516 | -30,3567 | <0,001 | 1.432.767 | 1.764.322 | 7,0176 | <0,001 | 1.184.651 | 1.004.305 | -6,8665 | <0,001 |
| SMA 5-150 | 6.572.778 | 3.073.266 | -31,0691 | <0,001 | 1.436.758 | 1.760.331 | 6,8477 | <0,001 | 1.181.769 | 1.007.187 | -6,6459 | <0,001 |
| SMA 1-200 | 6.623.149 | 3.022.895 | -32,0673 | <0,001 | 1.377.518 | 1.819.571 | 9,3769 | <0,001 | 1.181.121 | 1.007.835 | -6,5963 | <0,001 |
| SMA 2-200 | 6.607.762 | 3.038.282 | -31,7613 | <0,001 | 1.379.420 | 1.817.669 | 9,2955 | <0,001 | 1.179.855 | 1.009.101 | -6,4995 | <0,001 |
| TRB 50 | 6.476.343 | 3.169.701 | -29,1843 | <0,001 | 1.643.800 | 1.553.289 | -1,9108 | 0,0561 | 1.233.704 | 955.252 | -10,6416 | <0,001 |
| TRB 150 | 7.024.919 | 2.621.125 | -40,4239 | <0,001 | 1.433.004 | 1.764.085 | 7,0075 | <0,001 | 1.224.618 | 964.338 | -9,9390 | <0,001 |
| TRB 200 | 7.225.752 | 2.420.292 | -44,9203 | <0,001 | 1.403.435 | 1.793.654 | 8,2683 | <0,001 | 1.221.200 | 967.756 | -9,6751 | <0,001 |
| OBV 1-50 | 0 | 9.646.044 | 164,7422 | <0,001 | 1.916.713 | 1.280.376 | -13,5715 | <0,001 | 2.188.956 | 0 | -181,3892 | <0,001 |
| OBV 1-150 | 0 | 9.646.044 | 164,7422 | <0,001 | 1.899.570 | 1.297.519 | -12,8261 | <0,001 | 2.188.956 | 0 | -181,3892 | <0,001 |
| OBV 5-150 | 6.339.800 | 3.306.244 | -26,5695 | <0,001 | 1.251.824 | 1.945.265 | 14,8187 | <0,001 | 1.068.441 | 1.120.515 | 1,9778 | 0,0480 |
| OBV 1-200 | 0 | 9.646.044 | 164,7422 | <0,001 | 1.892.970 | 1.304.119 | -12,5398 | <0,001 | 2.188.956 | 0 | -181,3892 | <0,001 |
| OBV 2-200 | 6602609 | 3043435 | -31,6591 | <0,001 | 1168948 | 2028141 | 18,48552 | <0,001 | 1031867 | 1157089 | 4,761075 | <0,001 |
| BB | 482413 | 738828 | 6,066985 | <0,001 | 219395 | 159024 | -4,06932 | <0,001 | 144545 | 152993 | 0,854065 | 0,3931 |

Table 4. Applied trading rules to identify GR and LR

| Indicator | Reference 1 | Operator | Reference 2 | Decision | Description (time units) |
|---|---|---|---|---|---|
| Odean indicator | Average Price | > | Open Price | GR | Custom indicator |
| | Average Price | < | Open Price | LR | (1 unit) |
| SMA1-50 | Close Price | > | SMA50 | GR | Simple Moving Average |
| | Close Price | < | SMA50 | LR | (short 1, long 50) |
| SMA1-150 | Close Price | > | SMA150 | GR | Simple Moving Average |
| | Close Price | < | SMA150 | LR | (short 1, long 150) |
| SMA5-50 | SMA5 | > | SMA5-150 | GR | Simple Moving Average |
| | SMA5 | < | SMA5-150 | LR | (short 5, long 50) |
| SMA1-200 | Close Price | > | SMA200 | GR | Simple Moving Average |
| | Close Price | < | SMA200 | LR | (short 1, long 200) |
| SMA2-200 | SMA2 | > | SMA200 | GR | Simple Moving Average |
| | SMA2 | < | SMA200 | LR | (short 2, long 200) |
| TRB50 | Close Price | > | TRB50 mband | GR | Trading Range Breakout |
| | Close Price | < | TRB50 mband | LR | (50 units) |
| TRB150 | Close Price | > | TRB150 mband | GR | Trading Range Breakout |
| | Close Price | < | TRB150 mband | LR | (150 units) |
| TRB200 | Close Price | > | TRB200 mband | GR | Trading Range Breakout |
| | Close Price | < | TRB200 mband | LR | (200 units) |
| MACD | MACD | > | Zero | GR | Moving Average Convergence |
| | MACD | < | Zero | LR | Divergence (9 units) |
| ROC | ROC | > | Zero | GR | Rate Of Change |
| | ROC | < | Zero | LR | (10 units) |
| OBV1-50 | Close Price | > | OBV SMA50 | GR | On Balance Volume |
| | Close Price | < | OBV SMA50 | LR | (short 1, long 50) |
| OBV1-150 | Close Price | > | OBV SMA150 | GR | On Balance Volume |
| | Close Price | < | OBV SMA150 | LR | (short 1, long 150) |
| OBV5-150 | OBV SMA5 | > | OBV SMA150 | GR | On Balance Volume |
| | OBV SMA5 | < | OBV SMA150 | LR | (short 5, long 150) |
| OBV1-200 | Close Price | > | OBV SMA200 | GR | On Balance Volume |
| | Close Price | < | OBV SMA200 | LR | (short 1, long 200) |
| OBV2-200 | OBV SMA2 | > | OBV SMA200 | GR | On Balance Volume |
| | OBV SMA2 | < | OBV SMA200 | LR | (short 2, long 200) |
| RSI | RSI | >= | 50 | GR | Relative Strenght |
| | RSI | < | 50 | LR | Indicator (14 units) |
| BB | Close Price | < | BB low | GR | Boellinger Bands |
| | Close Price | > | BB high | LR | (20 units) |
| | [Otherwise] | = | [Neutral] | N | |

## Technical Indicator Definition

The following short descriptions and formulas are based on definitions given in [37,1] and [45] as well as the technical analysis library [15] underlying the used Python TA-lib.

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[15] https://www.ta-lib.org/, https://tulipindicators.org/

*SMA - Simple Moving Average* A SMA shows the average price of an asset or security over a specified period of time. It is a very common used smoothing function on time series data. The main parameter $n$ defines the time window for the calculation. The SMA applies equal weight on each price in comparison to exponential, triangular or variable moving averages using different weights.

$$sma_t = \frac{1}{n} \sum_{i=0}^{n-1} in_{t-i} \tag{1}$$

*TRB - Trading Range Breakout (Donchian Channel)* Trading Range Breakout systems generate buy and sell signals when the price moves out of the channel band, depending on the $n$ number of periods for the calculation. The goal of this indicator is to identify bullish and bearish extremes, the middle band is the average of the highest high and the lowest low for $n$ periods.

$$
\begin{aligned}
MC &= \frac{UC - LC}{2} \\
\text{where } UC &= \text{Highest High in last } n \text{ periods (upper channel),} \\
LC &= \text{Lowest Low in Last } n \text{ periods (lower channel),} \\
MC &= \text{middle channel,} \\
n &= \text{number of minutes, hours, days, weeks, months,} \\
periods &= \text{minutes, hours, days, weeks, months}
\end{aligned}
\tag{2}
$$

*MACD - Moving Average Convergence Divergence* The MACD indicator helps in following trends and takes three parameter, a short period $n$, a long period $m$, and a signal period $p$. It is calculated subtracting the short from the long period resulting in a value oscillating above and below zero, signalling market trend (above zero bullish, below zero bearish).

$$
\begin{aligned}
short_t &= ema(n, input) \\
long_t &= ema(m, input) \\
macd_t &= short_t - long_t \\
signal_t &= ema(p, macd_t) \\
histogram_t &= macd_t - signal_t
\end{aligned}
\tag{3}
$$

*EMA - Exponential Moving Average* The EMA applies a exponential smoothing function. It puts greater weight on the significance of the more recent price values and takes one parameter, the period $n$. Larger values for $n$ will result in higher smoothing effects while also creating more lag. The calculation initial value is setting the first EMA output to the first input. The relation for $0 < a \leq 1$ will be satisfied in the first step.

$$a = \frac{2}{n+1}$$
$$ema_t = (1-a)ema_{t-1} + (a)in_t \qquad (4)$$

*ROC - Rate of Change*  The ROC indicator calculates the change between the current price and the price $n$ bars ago, providing information on momentum as the speed of e.g. price change. It takes also one parameter for the period $n$.

$$roc_t = \frac{in_t - in_{t-n}}{in_{t-n}} \qquad (5)$$

*OBV - On Balance Volume*  The OBV indicator calculates the running total of volume by summing up in up-days and subtracted on down-days. It is a momentum indicator providing crowd sentiment information on potential upcoming price changes using trading volume.

$$obv_t = \begin{cases} obv_{t-1} + volume_t & \text{if } close_t > close_{t-1} \\ obv_{t-1} - volume_t & \text{if } close_t < close_{t-1} \\ 0 & \text{else} \end{cases} \qquad (6)$$

*RSI - Relative Strength Indicator*  The RSI is a momentum oscillator. It helps to identify bullish or bearish trends, using one parameter, the period $n$. A asset is assumed overbought when RSI is above 70% and oversold when below 30%.

$$up_t = \begin{cases} in_t - in_{t-1} & \text{if } in_t > in_{t-1} \\ 0 & \text{else} \end{cases}$$
$$down_t = \begin{cases} in_{t-1} - in_t & \text{if } in_t < in_{t-1} \\ 0 & \text{else} \end{cases}$$
$$sup_t = \frac{n-1}{n}sup_{t-1} + \frac{1}{n}up_t \qquad (7)$$
$$sdown_t = \frac{n-1}{n}sdown_{t-1} + \frac{1}{n}down_t$$
$$rsi_t = 100 - \frac{100}{1 + \frac{sup_t}{sdown_t}}$$

*BB - Boellinger Bands*  The BB indicator calculates a middle band (Simple Moving Average), as well as upper and lower bands. Those bands have an offset of the middle band. BB takes two parameters, the period $n$ and a scaling value $a$. The offset of the upper and lower bands of the middle band is defined by a standard deviations of the input value.

$$bbands_t^{middle} = \frac{1}{n} \sum_{i=0}^{n-1} in_{t-i}$$

$$bbands_t^{lower} = bbands_t^{middle} - a\sqrt{\frac{1}{n} \sum_{i=0}^{n-1} (in_{t-i} - bbands_t^{middle})^2} \qquad (8)$$

$$bands_t^{upper} = bbands_t^{middle} + a\sqrt{\frac{1}{n} \sum_{i=0}^{n-1} (in_{t-i} - bbands_t^{middle})^2}$$