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Are crypto currencies cryptic or a source for arbitrage? A genetic algorithm approach

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Are crypto currencies cryptic or a source for arbitrage? A genetic algorithm approach.

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27 July, 2021

Abstract

This paper aims to identify forex triangular arbitrage trading opportunities using a branch of evolutionary algorithms known as genetic algorithms (GAs) to derive insights into the volatility cryptocurrencies and stablecoins with the largest market cap. The triangular trade will be carried out as a 3 or more-tuple arbitrage play consisting of two or more cryptocurrencies and a fiat currency (the USD) that is used to enter and exit the trades. Our results show persistent tradable arbitrage for digital currencies of $2 for stablecoins and $5 for cryptocurrencies and $25 for stablecoin mix strategy. Triangular arbitrage trading yielded no arbitrage profits with the fiat currency strategy, as expected.

Keywords: cryptocurrency, arbitrage, genetic algorithms (GAs), evolutionary algorithms (EAs), trading strategies, optimization.

1 Introduction

Despite the relatively unregulated nature of cryptocurrency markets (Dyhrberg, 2016), they have remained a phenomenon that continues to strengthen even after the 2017 Bitcoin bubble. Indeed, following Bitcoin reaching a height of $320 billion in market capitalization in December 2017 and collapsing to a market cap of $16 billion by December 2018, the cryptocurrency markets have observed a resurgence. As of August 2020 Bitcoin, had regained a substantial amount of that market capitalization to sit at $218 billion and daily trading volume of $36.57 billion while still trending upwards. This resurgence is not only limited to Bitcoin. Other cryptocurrencies such as Ethereum, while not as pronounced as Bitcoin, have witnessed similar market cap growth. Tether, the stablecoin with the largest market capitalization, has seen almost exponential growth in its market capitalization since the 2017 Bitcoin bubble to sit at $14 billion and a daily trading volume of $55 billion (Cryptocurrency Prices, Charts And Market Capitalizations, 2020).

As these markets continue to grow, it will be important to understand the extent to which they become price-efficient, and in particular, how increased liquidity and trading might aid this efficiency. The efficient market hypothesis (EMH) states that asset prices reflect all available information, implying that we would expect it to be difficult, if not impossible, to "beat the market" consistently on a risk-adjusted basis since market prices should only react to new information. This paper uses genetic algorithms (GAs), a special evolutionary algorithm, to identify forex (FX) triangular arbitrage trading opportunities to derive insights into the volatility of cryptocurrencies and stablecoins with the largest market cap. Triangular arbitrage is a trading strategy with which a trader seeks to exploit discrepancies in quotes among three different currencies in the FX market.

Triangular arbitrage entails executing a three-step trading strategy involving the exchange of (1) the base currency for a second currency, (2) the second currency for a third currency, and (3) the third currency for the base currency. If market pricing discrepancies exist between the currencies, the trader will exploit the discrepancy during the second step of the trading strategy and generate arbitrage profits. In mature and efficient markets, these arbitrage opportunities from such trading should be rare. Traders acting on all available information would execute these trades and force prices to correct quickly - these corrections could take the form of arbitrage trades lasting only seconds or a few minutes. There may also be seasonality in these trades, such that price mismatches exist only at certain times of the day (Fenn et al., 2009).

Our paper relates to the growing body of literature assessing the efficiency of cryptocurrency markets. Shah and Zhang (2014) used a Bayesian regression model to estimate price changes in

bitcoin over the period between February and July 2014. While they omitted transaction costs from their analysis and assumed perfect flow of funds, they found evidence that significant trading returns were possible. Madan et al. (2015) found similar results using binomial generalized linear and random forest models. (Garcia & Schweitzer, 2015) used a vector autoregressive (VAR) model to predict daily returns in bitcoin. More recent research has utilised machine learning (ML), and artificial intelligence (AI) approaches to estimate cryptocurrencies asset returns. Jiang & Liang (2017) employed deep reinforcement learning to predict returns in cryptocurrencies. McNally et al. (2018) tested the performance of various deep learning models, such as long short-term memory (LSTM), in estimating bitcoin returns. Fischer & Krauss (2018) found results that challenged the semi-strong form of the EMH by employing random forest-based statistical arbitrage strategies on high-frequency data to estimate the returns of 40 cryptocurrencies. Ha et al. (2018), on the other hand, utilised genetic programming to identify attractive technical trading patterns on the Poloniex crypto-to-crypto exchange.

One commonality within the literature is that previous research has treated arbitrage or the trading of crypto assets in a fashion similar to equity trades. Jiang & Liang (2017) tried to optimise a portfolio of crypto assets using deep reinforcement learning while Rohrbach et al. (2017) looked for technical indicators to assess market momentum. In this paper, we instead employ a simple yet well-established foreign exchange (FX) trading strategy known as the triangular (or cross-currency or three-point) arbitrage (see (Aiba et al., 2002), (Carbaugh, 2005), (Pilbeam, 1998), and (Fenn et al., 2009)) with cryptocurrencies.

The cryptocurrency market has remained fairly unregulated and consists of large numbers of less sophisticated traders and relatively low trading volumes, which may be reflected in pricing inefficiencies that can potentially be detected and exploited by algorithm-based arbitrage strategies.

This paper is organized as follows: Section 2 gives an overview of genetic algorithms. Section 3 describes the data, the research method, along with the discussion on parameter setting for the GA. Followed by the results and discussions in Section 4. Finally, in Section 5, we conclude with our findings.

2 Research Method

2.1 Introduction to Genetic Algorithms

The challenge of finding an optimal triangular FX arbitrage becomes more complex as the length of the arbitrage increases. Hence, reaching the optimal solution becomes increasingly difficult as the size of the problem increases. Such types of optimization problems can be solved efficiently and quickly by optimization algorithms. Therefore, we have extended the triangular trade over multiple cryptocurrency pairs using Genetic Algorithms.

Genetic Algorithms (GAs) are a class of adaptive search and optimization techniques based on principles of natural evolution. They are typically used for solving optimization problems that do not have a well-defined exact solution. GAs are very effective in finding approximate solutions to complex problems and are based on Darwin's evolutionary theory (Goldberg & Holland, 1988). They are meta-heuristic algorithms inspired by the process of natural selection, which belong to a larger class of evolutionary algorithms.

GA is an adaptive search method based on population genetics. The GA represents the solution space using genetic coding of a feasible solution as a chromosome that defines an individual member of a population, (see Figure 1 for a schematic overview). Each candidate solution (called a "chromosome" or an "individual")[1] has a set of characteristics (called the "genes") that can be evolved and changed in order to reach an optimal solution.

[1] Throughout the paper, we have used chromosomes and individuals interchangeably.

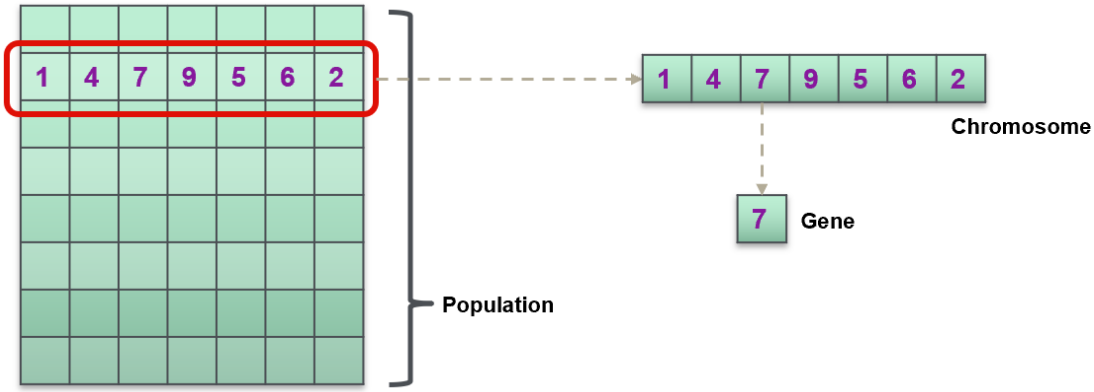


Figure 1: Population, chromosome and a gene of a genetic algorithm

The GA starts by choosing a random set defined as the initial population of individuals (a set of solutions) and evolves them in an iterative manner also known as generations. During each generation, every chromosome is allotted a fitness score based on a fitness function which is usually the objective of the optimization problem being solved. Fitter individuals from the current population are stochastically selected from the current population and undergo modifications (Saini, 2017) to compose a new population for the next generation. The selection and modification of chromosomes are performed using biologically-inspired operators, such as selection operator, crossover operator and mutation operator. The algorithm usually stops when either a maximum number of generations have been iterated over or a satisfactory level of fitness has been reached by the population. Figure 2 is an overview of GAs and every stage is explained in the following section.

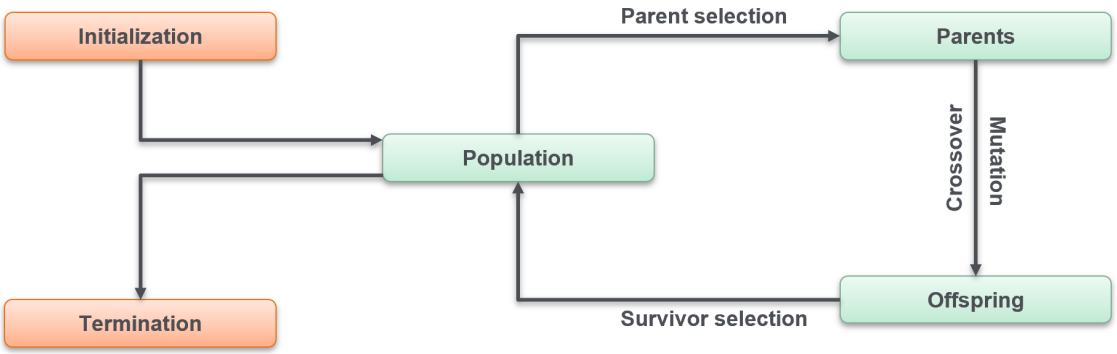


Figure 2. Flow chart of genetic algorithm (Nayak, 2020)

2.2 Data

We source the data used in this paper from two locations. The crypto and stablecoin data were obtained from the UK-based CryptoCompare, a global cryptocurrency market data hub offering an extensive depth of data across over 280 globally recognised exchanges representing real-time market and pricing data on an excess of 5,300 coins and 240,000 currency pairs. The CryptoCompare dataset also includes tick data, cryptocurrency trade data, order book data, blockchain and historical data, social data, reports and a suite of cryptocurrency indices. The CryptoCompare dataset also adheres to rigorous standards in order to safeguard data integrity, normalising global sources to ensure consistency and confidence in the market. Furthermore, CryptoCompare regularly reviews crypto exchanges, monitors for market abuse and takes regional anomalies and geographical movements into consideration to validate the integrity of the data. As such, we have confidence in the quality and validity of the data. The Fiat Data were obtained from the website www.histdate.com.

For this paper, we have used pricing data for cryptocurrencies and stablecoins across various exchanges like Kraken, Bittrex, Binance, Coinbase etc (see Appendix). We have selected pure cryptocurrencies and stablecoins with the highest market capitalization. We have extracted the data for every minute starting from 1st January 2020 at 0000 hours till 31st March 2020 2359 hours. We have further divided the data into three groups. The first group contains "pure"

cryptocurrencies, the second group contains stablecoins[2], and the third group contains a mix of all the pure cryptocurrencies and stablecoins.

One limitation that we encountered with the data was that the pricing information was not available for every cryptocurrency pair. Therefore, we have selected an intermediate currency that had the pricing data available against every other currency to generate the pricing for the missing pairs. This resulted in two trades instead of one and did not have any major impacts on the end result except that of the nominal transaction fee.

Our research also assumes that we are free to trade currencies between different exchanges so that we have access to top currencies and are not just limited to the currencies available at a single exchange. This way, we are estimating an optimal trading strategy which might not be attainable in the real world due to limitations such as added cost of trading currencies between exchanges and availability of specific currencies at different exchanges.

2.3 Chromosome Representation

Potential solutions are encoded in a chromosome as shown in Figure 1. For example, we consider a sequence of exchange taken at random with a maximum of 7 currencies $\{x_1, x_2, x_3, x_4, x_5, x_6, x_7\}$. Every gene is encoded with an integer between 1 and 7, where 1 = Cardano (ADA), 2 = Bitcoin Cash (BCH), 3 = Bitcoin (BTC) , 4 = Ethereum (ETH), 5 = Algorand (ALGO) , 6 = Bitcoin Diamond (BCD) , 7 = Dogecoin (DOGE). We look for a sequence that will allow us to enter the exchange with 1 USD and exit with y USD where $0 \leq y \leq \infty$. We say that the arbitrage resulted in a profit if $y > 1$ and resulted in a loss if $0 < y < 1$. For example, the chromosome {1,3,4,7,5,6,2} encodes the following sequence of currencies {ADA, BTC, ETH, DOGE, ALGO, BCD, BCH} and represent the arbitrage trading strategy as: {USD/ADA, ADA/BTC, BTC/ETH, ETH/DOGE, DOGE/ALGO, ALGO/BCD, BCD/BCH, BCH/USD}. Every time a currency is exchanged we apply a transaction cost which was equal to one the most common transaction fees across various exchanges that were observed for trading currencies, $k * 0.01$, $k = \{0.04, 0.2, 0.5, 5.9\}$. The length of the

[2] Stablecoins are a class of cryptocurrencies that attempt to offer price stability and are backed by one or more reserve assets. Pure cryptocurrencies on the other hand are not backed by an underlying asset but whose prices are determined by market trading.

chromosome can be changed. Section 4.1 discusses how the length of the chromosome affects the overall profits.

2.4 Fitness Function

The fitness function is the objective function of the optimization problem. A fitness score is associated with each individual in the population which indicates the quality of the solution (i.e., trading strategy) represented by that individual. This score will determine which individuals will pass on their traits to the offspring in the next generation. We have applied the following fitness function:

$$fitness\left(chromosome_i\right) = y$$

Here, $chromosome_i \in Population_j$, $1 \leq i \leq N$ and $1 \leq j \leq G$ where N in the number of chromosomes in the population, G is the number of generations for which the GA evolves, and y is the final amount of USD that we obtain using the arbitrage sequence suggested by the chromosome. It indicates the profit or loss made by the arbitrage sequence.

2.5 Population Initialization

The algorithm starts by choosing a random set of chromosomes defined as the initial population and succeeds them generationally. One constraint that we apply for every individual in the population is that no gene of the chromosome is duplicated, which means that no cryptocurrency is traded more than once in an arbitrage. We impose the constraint that a sequence of currency pairs that constitute a triangular arbitrage trade strategy is valid if and only if that sequence begins and ends with currency pairs that include USD. Moreover, we exclude chromosomes that have USD involved pairs anywhere else in the sequence. This means that each chromosome consists of only two currency pairs with USD and all intermediate currency pairs are exclusively prue cryptocurrency or stablecoin coin currency pairs. Without this constraint, we would effectively be merging multiple strategies into one.

2.5.1 Population Size

The algorithm starts with the random initialization of the chromosome. Since, most of the chromosomes in the population result in a trading that is not profitable, we keep the population size quite large. This increases the probability of having at-least a few chromosomes in the population that result in a profitable trading strategy. As such, we set the population size to 500 in order to include more profitable chromosomes. While a large population size increases the computational search time needed to find the optimal or near-optimal solution, it increases the probability that the initial state population will contain an individual representing an optimal solution. A large population, in this case, will have a greater number of potentially profitable chromosomes and a higher chance these chromosomes are selected for further processing.

2.5.2 Number of Generations

To estimate the number of generations that the GA should run for, we compare the fitness score of the fittest chromosome in every generation. Figures 3 and 4 illustrate the increase of the fitness score with increasing generations for pure crypto currencies and a mix of pure and stable cryptocurrencies. It is evident from Figure 3 that for pure cryptocurrencies, the solution converges after 30 generations. Similarly, for the mix of pure cryptocurrencies and stablecoins, the algorithm converges at around 80 generations (see Figure 4). The reason for the higher number of generations needed for convergence in this case is that the mix of pure cryptocurrencies and stablecoins have a higher number of cryptocurrencies and hence more possible trading strategies in the search space that the GA needs to process.

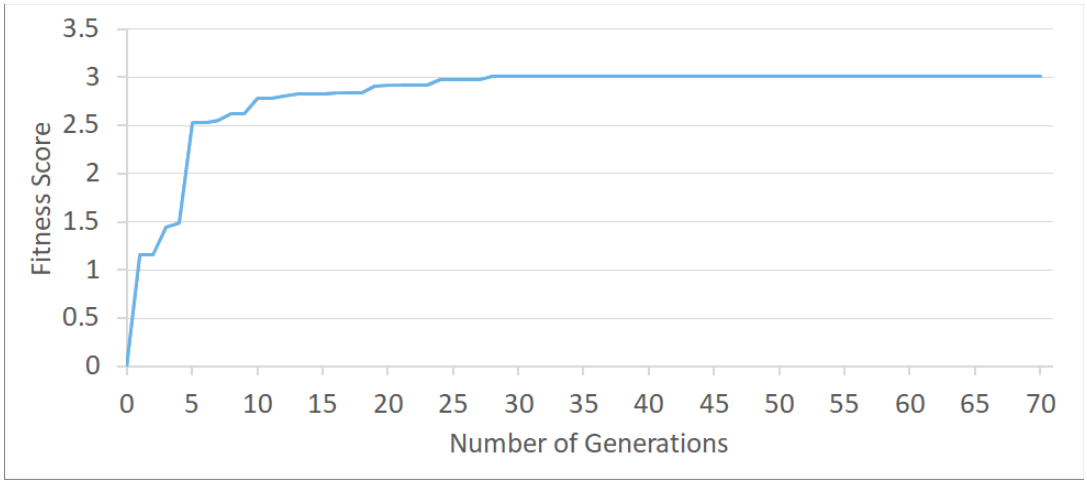


Figure 3: Fitness Value vs Number of Generations for pure cryptocurrencies

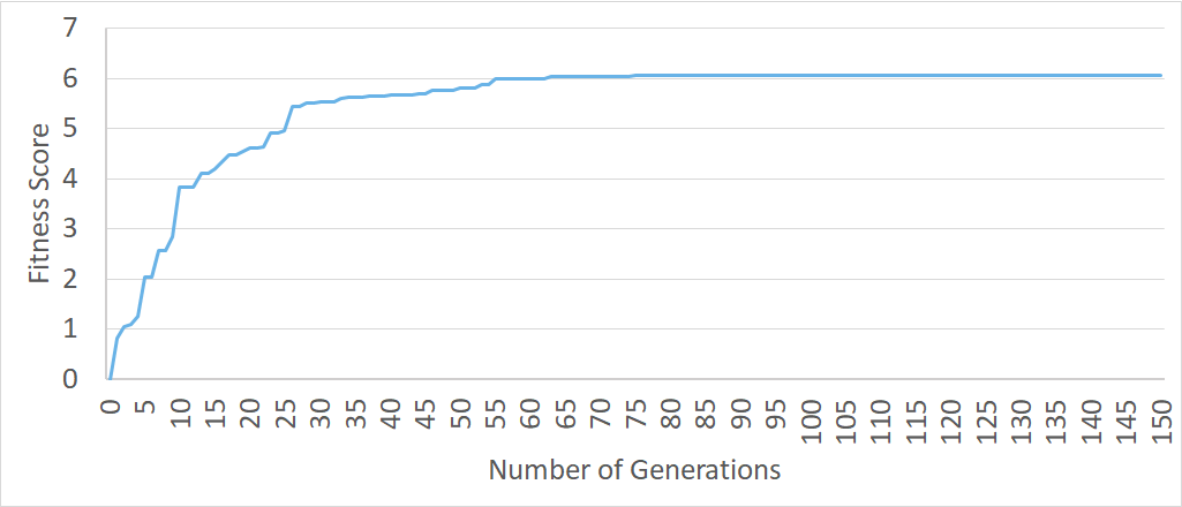


Figure 4: Fitness Value vs Number of Generations for pure and stable cryptocurrencies

2.6 Parent Selection

The first stage towards evolution is the selection of the parent which will pass on its traits to the successive generation. The fitness score helps in this selection as the parents with higher fitness have a better chance of getting selected. The parents are selected using the Tournament Selection method. A desired number of parents selected together form a mating pool.

2.6.1 Tournament Selection

Tournament selection is one of the most common parent selection methods in genetic algorithms (*Genetic Algorithms - Fundamentals*). In this method $k$individuals are selected randomly from the larger population and the selected individuals compete against each other. The individual with the highest fitness score wins and will pass its genes on to the population of the next generation. The number of individuals competing in each tournament is referred to as the *tournament size*. The tournament size can be used to adjust the selection pressure. If it is larger, weaker individuals will have a smaller chance of getting selected. This process is repeated until the mating pool is full i.e., the desired number of parents have been selected for mating or recombination. (Figure 5) illustrates the mechanism of tournament selection where the tournament size is set to three.

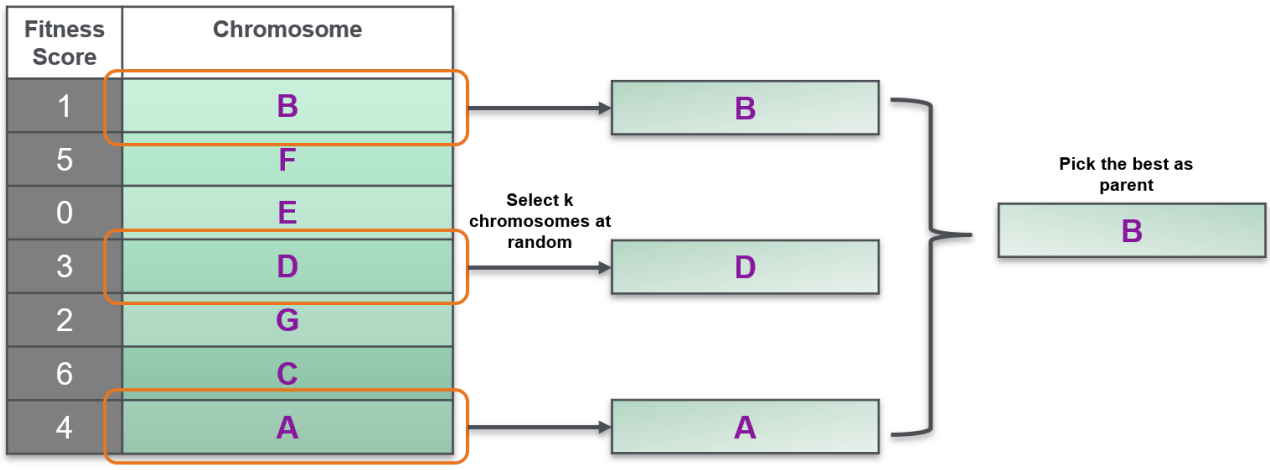


Figure 5: Tournament selection

In tournament selection, there is a competition amongst k selected individuals to determine the individuals with the highest fitness value. All individuals have an equal chance to be chosen, which ensures diversity in the selection process. We have set the tournament size to 10 as it increases the chances that the profitable individuals are selected for further propagation.

2.7 Crossover

Once the mating pool has been filled, the parents are set to cross (mate) their traits to generate offspring (new individuals) that will be a part of the population of the next generation of chromosomes. This involves crossing two parents at a time to generate two offspring. This process of recombination aims to produce a new population with a higher average fitness value compared to the previous population. This results in the exploitation of the search space. The probability with which the individuals undergo crossover can be configured. For this study to choose to implement the ordered crossover (OX).

2.7.1 Ordered Crossover

The ordered crossover preserves the relative order of the elements in the parent chromosomes, ensuring that the genes are not duplicated within an individual. This is done to obtain a trading strategy which does not have repeated cryptocurrencies and ensures that we start and end each trading strategy in USD (Figure 6). *Offspring1* inherits genes of a random segment from *Parent1*, in the same order and position. The remaining elements are inherited from *Parent2* in the order they appear in *Parent2* starting from the endpoint of the segment, wrapping around the list and skipping all the genes that are already present in *Offspring1*. *Offspring2* is produced by reversing the role of the parents.

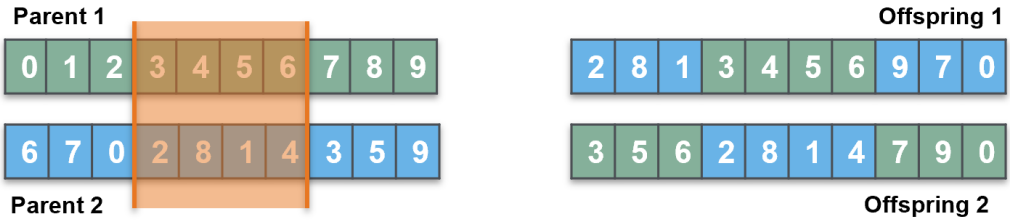


Figure 6: Ordered crossover

2.8 Mutation

After the offspring are generated through crossover, they go through a subsequent process of mutation. Unlike crossover, mutation is performed on a single chromosome. By performing random changes in the chromosomes, mutation ensures that new parts of the search space can be reached, thus exploring the search space for better solutions. They ensure genetic diversity from one generation to another. The probability with which mutation will take place can be configured. For this study, we have applied the Random Resetting mutation.

In the Random Resetting mutation, one gene is selected at random and then a value from a set of permissible values is assigned to that gene (Figure 7). In this case, a value represents a cryptocurrency and is replaced by another cryptocurrency that is not already present in the chromosome.

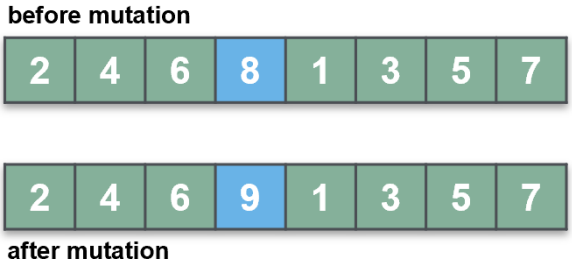


Figure 7: Random resetting mutation

2.9 Crossover and Mutation Probability

The crossover probability sets the rate at which two chromosomes exchange some of their parts. A 100% crossover probability means that all offspring are a result of crossover, and a 0% crossover probability means that the new generation is exactly copied from the previous generation (except those resulting from the mutation process). The mutation probability determines the rate at which chromosomes are mutated in one generation. Mutation prevents the GA from converging to local optimum[3], but if it is done at a high enough rate, the GA turns into a random search. Previous studies, such as (Muhlenbein & Schlierkamp-Voosen, 1993), have shown that the crossover probability depends on the size of the population and small mutation rates (1%-15%) have a greater effect on small size populations. For larger populations, higher crossover and mutation rates are desirable. We have set a high level for the probability of crossover (80%) and medium level for the probability of mutation (30%).

2.10 Survivor Selection

The survivor pool contains the individual that will be passed on to the next generation. This process usually considers only the fitter chromosomes. There are two kinds of chromosomes that make it to the next generation: (1) fitter chromosomes of the current generation (2) offspring that are generated by crossover and mutation. As suggested in Fernández-Pérez et al. 2012, in every generation we replace half of the population. We swap the least favourable individuals with new offsprings. This process increases the diversity of the population and ensures that non-profitable arbitrage solutions are swapped out from the population, leaving a healthier population at every generation.

The value of all the control parameters are summarized in Table 1.

[3] For a detailed discussion on local and global optima visit https://machinelearningmastery.com/local-optimization-versus-global-optimization/

Parameter Type	Value
Population size	500
Generations	50
Crossover probability	0.8
Tournament size	10
Number of offspring	250
Mutation probability	0.3

Table 1: Control Parameters

3 Results

3.1 Effect of chromosome length on the fitness of the solution

The arbitrage trades are segregated across three strategies. The first strategy contains 31 pure cryptocurrencies, the second contains only 22 stablecoins, and the third contains a mix of all the cryptocurrencies and stablecoins. Furthermore, given the objective of the arbitrage is to optimise profits over the number of trades within each trading strategy, we employ a series of ANOVA tests on samples of solutions generated by the GA with varying chromosome lengths to determine the optimal number of trades for each strategy and the statistical significance of the obtained arbitrage profits.

Under the ANOVA, we assume that the results of the GA follow a normal distribution, and consider three possible sizes of chromosomes for each set of samples. Let $\overline{X}_1$, $\overline{X}_2$ and $\overline{X}_3$ be the mean on n independent runs of the GA on a single time instance, where the chromosome length are c_1, c_2

and $c_3$respectively. The null hypothesis states the $H_0: \overline{X}_1 = \overline{X}_2 = \overline{X}_3$, and we reject the null hypothesis when $F > f$, where $F$is the F-ratio and f is the F-critical ratio.

3.1.1 Pure cryptocurrencies

Tables 2 to 4 summarise the results of ANOVA tests on solutions generated for the pure cryptocurrency strategy with chromosome lengths of $\{c_1 = 5,\ c_2 = 7c_3 = 10\}$, $\{\ c_1 = 7,\ c_2 = 10$ and $c_3 = 15\}$, and $\{c_1 = 10,\ c_2 = 15$ and $c_3 = 20\}$ respectively. In all cases, we observe a p-value of less than 0.05 and F-ratios of 13.70002, 6.7633511, and 56.84031 such that in all cases $F > f$ and we accordingly reject the null hypothesis H_0. In other words, in all cases under the pure cryptocurrency strategy, our results indicate that the variations in the performance of the arbitrage strategy is explained by the difference in length of the chromosomes.

Source of variation	Degree of freedom	Sum of squares	Mean square	F	$p - value$	f
Between groups	2	1.915486	0.957743	**13.70002**	**0.000014**	**3.158843**
Within groups	57	3.984763	0.069908			

Table 2: ANOVA summary table for pure cryptocurrencies when $c_1 = 5$, $c_2 = 7$ and $c_3 = 10$ and the number of runs *n* is 20.

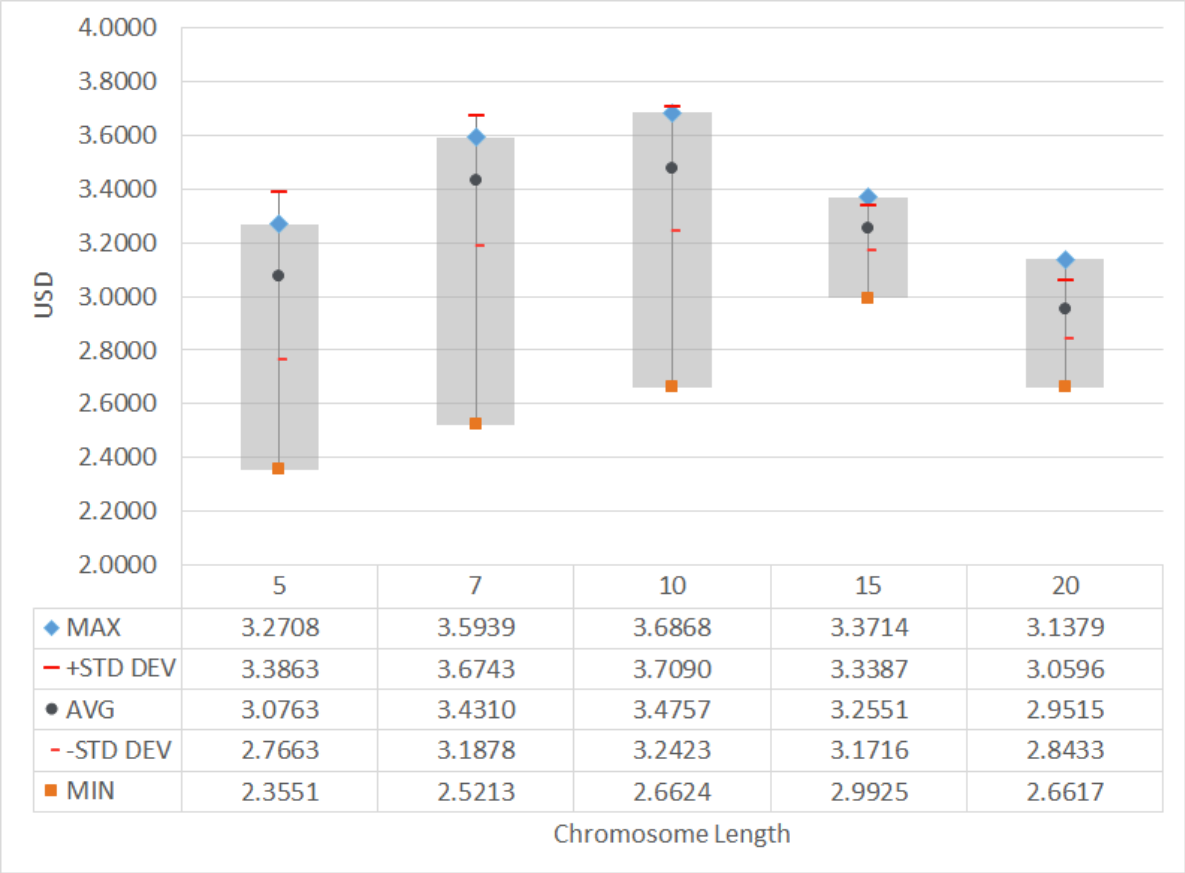
Source of variation	Degree of freedom	Sum of squares	Mean square	F	$p - value$	f
Between groups	2	0.543749	0.271874	**6.7633511**	**0.002314**	**3.158843**
Within groups	57	2.291296	0.040198			

Table 3: ANOVA summary table for pure cryptocurrencies when $c_1 = 7$, $c_2 = 10$ and $c_3 = 15$and the number of runs *n* is 20.

Source of variation	Degree of freedom	Sum of squares	Mean square	F	$p - value$	f
Between groups	2	2.77087	1.385435	**56.84031**	**0.00001**	**3.158843**
Within groups	57	1.389327	0.024374			

Table 4: ANOVA summary table for pure cryptocurrencies when $c_1 = 10$, $c_2 = 15$ and $c_3 = 20$ and the number of runs *n* is 20.

Figure 7 compares the minimum, maximum, average and standard deviation of the profits obtained on a single time instance over 20 runs for varying chromosome length for pure cryptocurrencies. It forms the basis of our selection of the optimal selection of chromosome length or trade chain. Note that we select the optimal length based on the largest average arbitrage profits. We could have also selected the optimal chromosome length based on the highest mean arbitrage profits with the smallest distance between the minimum and maximum profits. We observe arbitrage profits increase as the chromosome length increases. Moreover, given our selection of chromosome lengths, profits are observed to reach a peak at a chromosome length of 10 where the volatility, as captured by the standard deviation, in arbitrage returns is also minimized. Increasing the chromosome length beyond 10 results in declining profitability and increased volatility in returns. These declining arbitrage returns as the chromone length increases beyond 10 is an indication of diminishing returns stemming from two things: Firstly, as the chromosome length increases, we move closer to the boundaries of the total population of currencies we trade across meaning rather than optimizing a choice of currencies we simply rearrange the order of trades. Second, transaction costs at each currency pair trade introduce and enforce diminishing returns as chromosome length is increased.



	5	7	10	15	20
MAX	3.2708	3.5939	3.6868	3.3714	3.1379
+STD DEV	3.3863	3.6743	3.7090	3.3387	3.0596
AVG	3.0763	3.4310	3.4757	3.2551	2.9515
-STD DEV	2.7663	3.1878	3.2423	3.1716	2.8433
MIN	2.3551	2.5213	2.6624	2.9925	2.6617

Figure 7: Average, Minimum, Maximum, Standard Deviation graph for pure cryptocurrencies with varying chromosome lengths.

3.1.2 Stablecoins

Next, we apply the ANOVA test to the stablecoin strategy consisting of 22 different stablecoins. As with the pure cryptocurrency strategy, we assess the statistical significance of arbitrage performance on trades consisting of $\{c_1 = 5, c_2 = 7c_3 = 10\}$, $\{c_1 = 7, c_2 = 10$ and $c_3 = 15\}$, and $\{c_1 = 10, c_2 = 15$ and $c_3 = 20\}$ currency pairs. The results are summarised in Tables 5 to 7. In all three cases, we observe a p-value less than 0.05 and respective F-ratios of 3.878943, 566.9541, and 35.98564 with $F > f$. As such, we can reject the null hypothesis and conclude that chromosome length does impact arbitrage performance in the stablecoin strategy.

The results further point to an optimal trade length for the stablecoin strategy that consists of 7 currency pairs (see Figure 8). Similar to pure cryptocurrencies, arbitrage profits have the lowest

volatility at the optimal trade length and exhibit diminishing returns once transaction costs outweigh the marginal gains from increasing the chromosome length. As with pure cryptocurrencies, it is also noteworthy that arbitrage returns at the optimal trade length exhibit the lower volatility in those returns. It is worth noting that the returns and the standard deviation is lower for stablecoins than pure cryptocurrencies.

Source of variation	Degree of freedom	Sum of squares	Mean square	F	$p - value$	f
Between groups	2	0.068796	0.034398	**3.878943**	**.026339**	**3.158843**
Within groups	57	0.505473	0.008868			

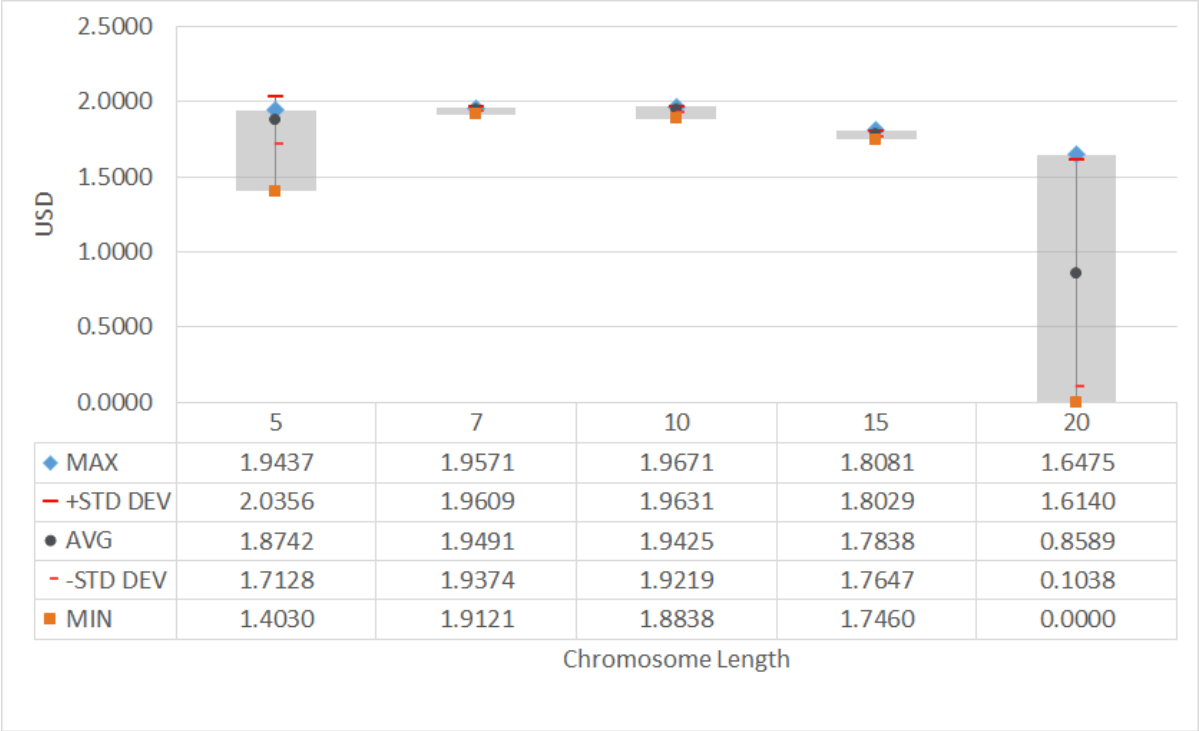
Table 5: ANOVA summary table for stablecoins when $c_1 = 5$, $c_2 = 7$ and $c_3 = 10$.

Source of variation	Degree of freedom	Sum of squares	Mean square	F	$p - value$	f
Between groups	2	0.350419	0.17521	**566.9541**	**0.00001**	**3.158843**
Within groups	57	0.017615	0.000309			

Table 6: ANOVA summary table for stablecoins when $c_1 = 7$, $c_2 = 10$ and $c_3 = 15$.

Source of variation	Degree of freedom	Sum of squares	Mean square	F	$p - value$	f
Between groups	2	13.69725	6.848627	**35.98564**	**0.00001**	**3.158843**
Within groups	57	10.84799	0.190316			

Table 7: ANOVA summary table for stablecoins when $c_1 = 10$, $c_2 = 15$ and $c_3 = 20$.



	5	7	10	15	20
MAX	1.9437	1.9571	1.9671	1.8081	1.6475
+STD DEV	2.0356	1.9609	1.9631	1.8029	1.6140
AVG	1.8742	1.9491	1.9425	1.7838	0.8589
-STD DEV	1.7128	1.9374	1.9219	1.7647	0.1038
MIN	1.4030	1.9121	1.8838	1.7460	0.0000

Figure 8: Average, Minimum, Maximum, Standard Deviation graph for stablecoins with varying chromosome lengths.

3.1.3 Pure cryptocurrency and Stablecoin Mix

Finally, we conduct the ANOVA test on the asset mix strategy consisting of 53 pure cryptocurrencies and stablecoins across the same grouping of trade/chromosome lengths as used for both the pure cryptocurrency and stablecoin strategies.[4] As illustrated in results summarized in Tables 8 to 10, we are able to reject the null hypothesis that arbitrage returns are not driven by the number of currency pairs used in the strategy based on observed p-values less than 0.05 and F-ratios 33.23054, 29.741, and 19.73295 for which $F > f$.

[4]The same 31 pure cryptocurrencies and 22 stablecoins previously used. Since GA is a global search heuristic algorithm, they find the optimal solution for any subset of the initial set of currencies.

Source of variation	Degree of freedom	Sum of squares	Mean square	F	$p - value$	f
Between groups	2	27.10205	13.55103	**33.23054**	**0.00001**	**3.158843**
Within groups	57	23.2439	0.40778			

Table 8: ANOVA summary table for the mix of pure cryptocurrencies and stablecoins when $c_1 = 5$, $c_2 = 7$ and $c_3 = 10$.

Source of variation	Degree of freedom	Sum of squares	Mean square	F	$p - value$	f
Between groups	2	34.7727	17.3863	**29.741**	**0.00001**	**3.158843**
Within groups	57	33.3217	0.5846			

Table 9: ANOVA summary table for the mix of pure cryptocurrencies and stablecoins when $c_1 = 7$, $c_2 = 10$ and $c_3 = 15$.

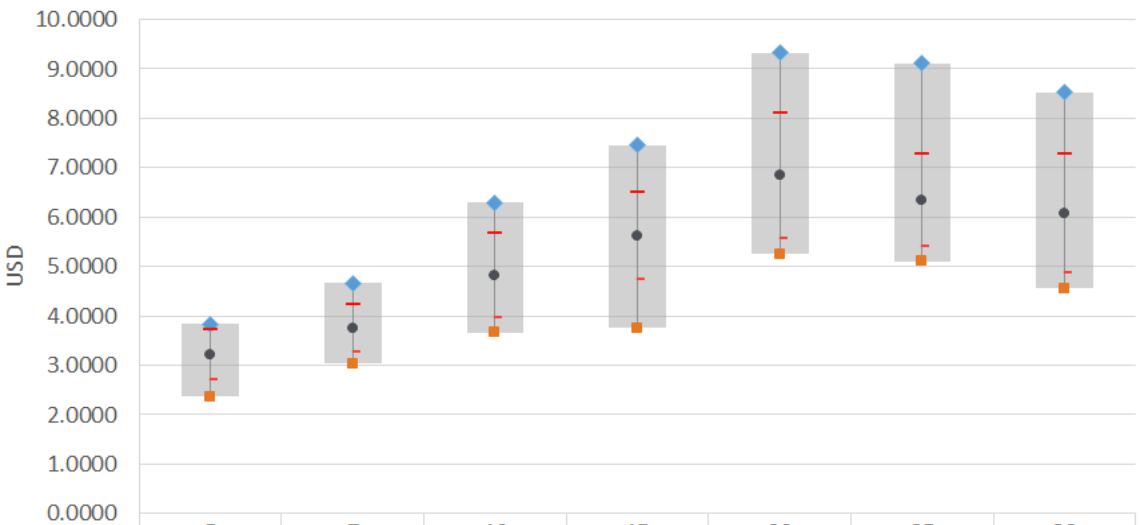
Source of variation	Degree of freedom	Sum of squares	Mean square	F	$p - value$	f
Between groups	2	41.21839	20.6092	**19.73295**	**0.000135**	**3.158843**
Within groups	57	59.53111	41.21839			

Table 10: ANOVA summary table for the mix of pure cryptocurrencies and stablecoins when $c_1 = 10$, $c_2 = 15$ and $c_3 = 20$.

With regards to the selection of the optimal number of currency pairs traded within the mixed strategy as summarised in Figure 9, the results suggest that arbitrage returns peak at a chromosome length of 20. In other words, by trading both pure cryptocurrencies and stablecoins in a mixed strategy, a rational trader should, in theory, be able to continue improving on profitability by trading more currency pairs long after such trading would be hit by diminishing returns when trading only the pure cryptocurrency or stablecoin strategy. Specifically, the arbitrageur is able to acquire arbitrage profits from the mixed strategy that are 1.97 or 3.53 times those from only trading pure cryptocurrencies or stablecoins. Furthermore, we observe that the worst performing choice of chromosome length, with mean profits of $3.21, in the mixed strategy

is relatively close in performance to the optimal choice of the number of trading pairs in the pure cryptocurrency only strategy with a mean profit of $3.48.

Despite the performance of the mixed strategy, a particularly interesting point of note is that, unlike the pure cryptocurrency or stablecoin strategies, the volatility in observable profits rises as arbitrage profits are maximized. Indeed, at its optimal, the mixed strategy records a volatility of $1.27 as compared to $0.02 for only pure cryptocurrencies and $0.01 for only stablecoins. While on paper this may suggest that the mixed strategy is inherently riskier than the single segment strategies, it is also an indication that there is not the convergence on a single solution of chromosome constituents as there exists in the other strategies. That is to say, by employing the mixed strategy, not only is there a larger pool of currency pairs to trade and earn arbitrage profits on, the arbitrageur is able to find multiple unique mixes of currency pairs that are profitable.



	5	7	10	15	20	25	30
MAX	3.8367	4.6621	6.2964	7.4510	9.3223	9.1133	8.5197
+STD DEV	3.7151	4.2394	5.6843	6.5049	8.1103	7.2696	7.2669
AVG	3.2076	3.7593	4.8267	5.6172	6.8414	6.3391	6.0670
-STD DEV	2.7001	3.2793	3.9692	4.7295	5.5726	5.4087	4.8672
MIN	2.3679	3.0355	3.6667	3.7521	5.2501	5.1098	4.5572

Figure 9: Average, Minimum, Maximum, Standard Deviation graph for pure cryptocurrencies and stablecoins mix with varying chromosome lengths.

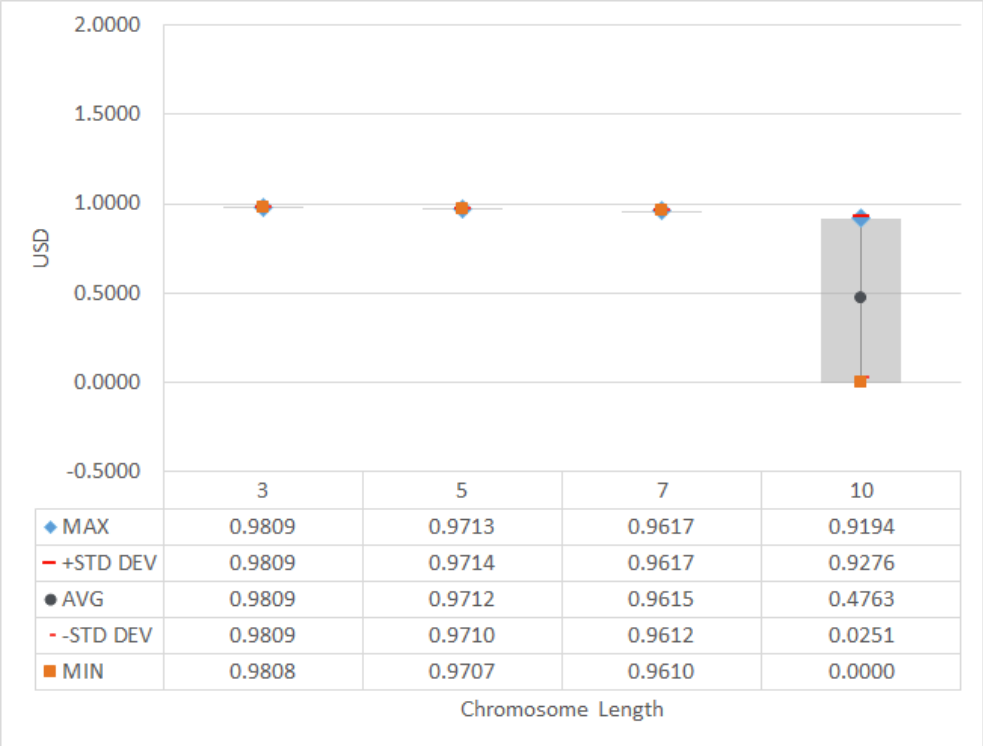
3.1.4 Fiat Currencies

As a comparative baseline, we test the performance of the GA in a strategy of 19 fiat currencies. As with the digital currency strategies, we employ the ANOVA to determine both the optimal number of trading pairs and the statistical significance of arbitrage profits obtained. We conduct the ANOVA on samples of solutions generated by chromosomes of lengths $c_1 = 3, c_2 = 5, c_3 = 7$ and $c_4 = 10$ as summarised in Table 11. With a p-value of 0.00001 at an F-ratio of 21.05721 and $F > f$, we reject the null hypothesis and conclude that arbitrage profits are impacted by the number of currency pairs traded within the strategy.

Source of variation	Degree of freedom	Sum of squares	Mean square	F	$p - value$	f
Between groups	3	3.3707	1.1236	**21.05421**	**0.00001**	**2.723**
Within groups	76	4.0552	0.0534			

Table 11: ANOVA summary table for the mix of pure cryptocurrencies and stablecoins when $c_1 = 3, c_2 = 5, c_3 = 7$ and $c_4 = 10$

From Figure 10 we observe that the optimal number of currency pairs trading within the fiat currency strategy is three, and as the chromosome length increases beyond this, the arbitrage strategy generates deeper losses. This contrasts with the results of cryptocurrencies and stablecoins where transaction costs only begin to diminish trading profits when trading on chromosome lengths of at least 10. Moreover, not only can arbitrage profits be expanded by increasing the number of digital currencies trades, at the minimum triangular arbitrage strategy trade length of 3 currency pairs, arbitrage returns are significantly higher in digital currencies than in fiat. Indeed, the observation of losses trading the triangle in fiat is an indication of less price misalignment in fiat currency markets than in digital currency trading.

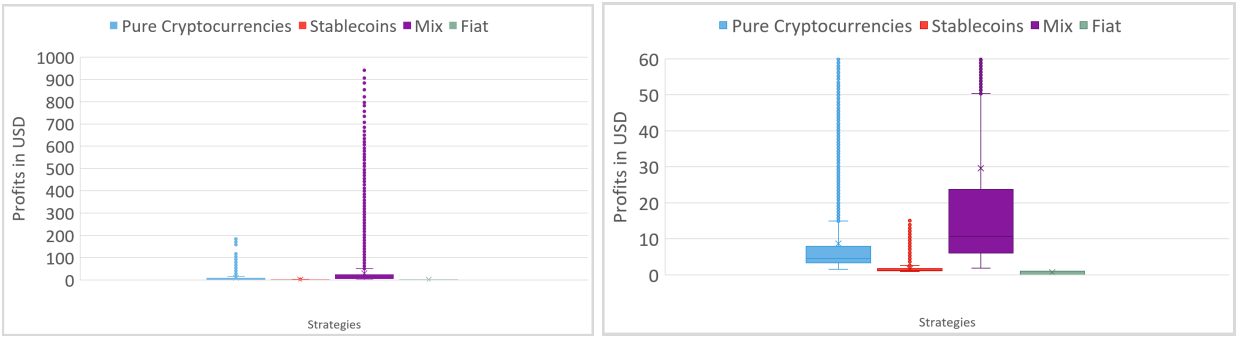


	3	5	7	10
MAX	0.9809	0.9713	0.9617	0.9194
+STD DEV	0.9809	0.9714	0.9617	0.9276
AVG	0.9809	0.9712	0.9615	0.4763
-STD DEV	0.9809	0.9710	0.9612	0.0251
MIN	0.9808	0.9707	0.9610	0.0000

Figure 10: Average, Minimum, Maximum, Standard Deviation graph for fiat currency with varying chromosome lengths.

3.2 Temporal Sustainability of Arbitrage Profits

Based on the optimal selection of the number of traded pairs employed within each trading strategy we assess the sustainability of arbitrage profits over time. Accordingly, we assess returns between January and March.



a) Full graph **b) Zoomed in version**

Figure 11: Profits for different strategies generated in January, 2020.

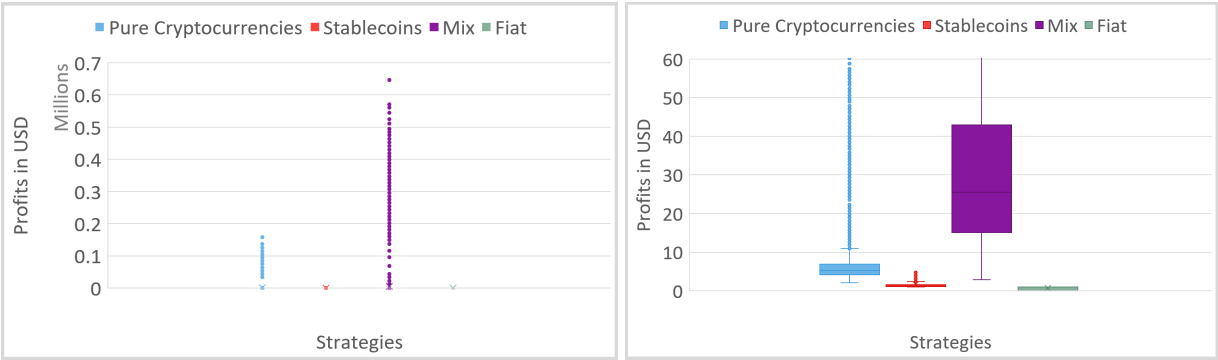
Figure 11 compares the profits generated under the four strategies during the month of January, 2020. Most notable in these results are that the outliers in arbitrage profits are consistent with the increasing magnitude of volatility observed at the optimal chromosome length selection as we move from stablecoins to the mixed strategy. Indeed, the mix of pure cryptocurrencies and stablecoins generate profits at the extreme of approximately US$950, in comparison to the US$195 and US$16 arbitrage profits potentially attainable in pure cryptocurrencies and stablecoins respectively. Notwithstanding the outliers, the three digital currency based arbitrage strategies on average record a modest yet lucrative return on investment. With the mixed strategy, we observe that 50% of arbitrage trades in January would have returned US$11 or less and 75% less than US$25 on the US$1 trade. For the pure cryptocurrency strategy, the observed median arbitrage profit is US$5 on the US$1 outlay, whilst for the stablecoin strategy this drops to just US$2 on the US$1 investment. By contrast, the Fiat strategy barely breaks even, losing approximately 2% or more of the initial US$1 outlay.

As illustrated in Figure 12, a similar pattern in arbitrage profits is observed in February as in January. The Fiat strategy remains unprofitable while the pure cryptocurrency and stablecoin strategies both give rise to similar profits on average as in January. Indeed, we observe a contracting of profits in these two strategies with the pure cryptocurrency strategy. We observe maximum profits contract from US$17 to US$11 and so to the inter-quartile range as 75% of profits in February falling below US$6 compared to US$8 in January. The same is observed for the stablecoin strategy with maximum profits dropping from US$2 to US$1.5 between January and February trading. By contrast, arbitrage profits under the mixed strategy expand between January and February trading with the strategy returning on average US$26 on the $1 investment

compared to the US$11 median profits in January. Likewise, 75% of profits from the mixed strategy are US$43 or less which is a 72% increase on the strategy's January profitability.

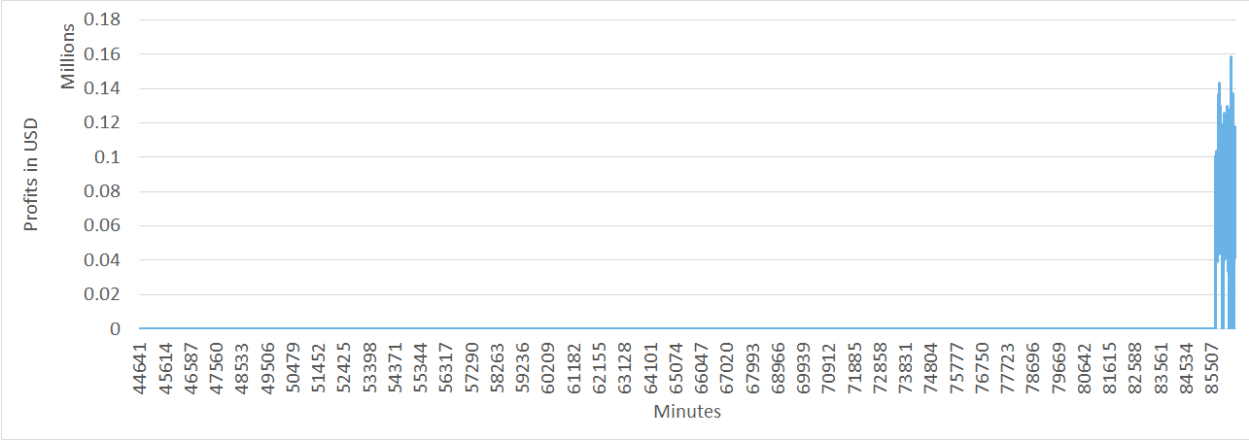
The results also show an explosion in the observable outliers from US$950 and US$195 for the mixed and pure cryptocurrency strategies respectively in January to US$700,000 and US$160,000 in February. Upon closer inspection as seen in Figure 13, it can be seen that these explosions occur at the end of February rather than being indicative of February. When contrasting these explosive outliers in the mixed and pure cryptocurrency strategies to those of the stablecoin strategy, we see the profitability of the stablecoin strategy become more compact; dropping from an extreme tail event of US$15 in January to just under US$5 in February.

Since we are using intermediate currencies to bridge between currency pairs that are not tradable, the results show price misalignments and extreme profits. These results are indicative of the purely theoretical limits of the profits that can be obtained. In practice, the ability to fill the order books will result in most of these trades to be unattainable.

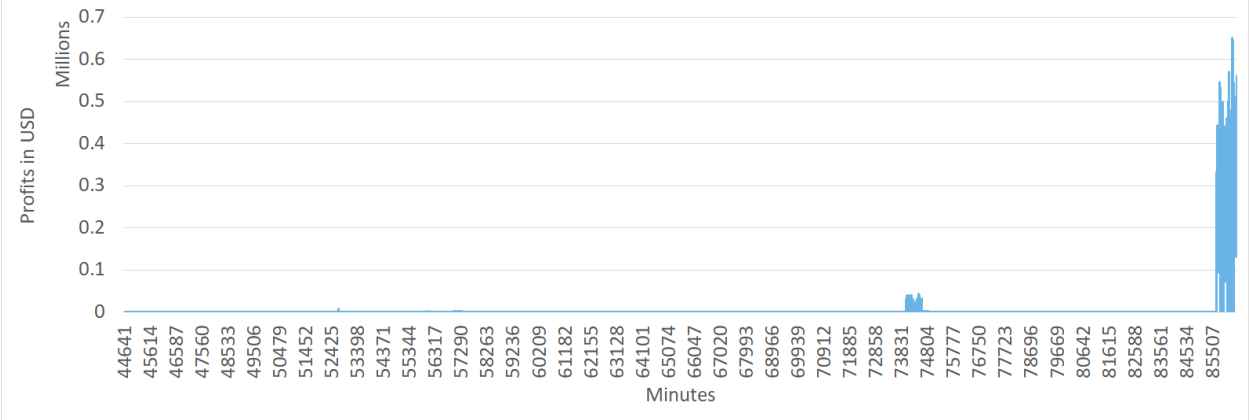


a) Full graph **b) Zoomed in version**

Figure 12: Profits generated in February, 2020



a) Pure cryptocurrencies



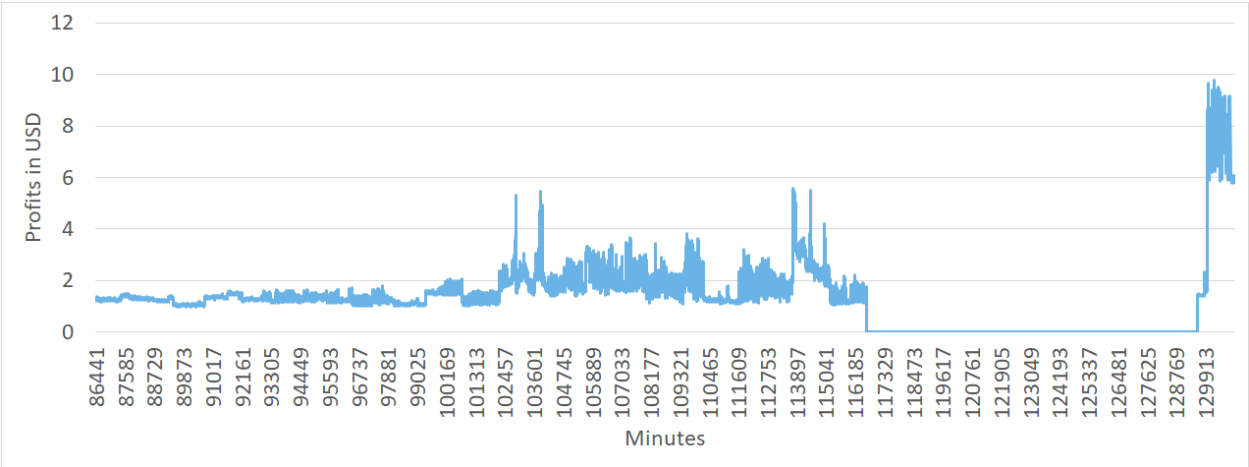
b) Mix of cryptocurrencies and stablecoins

Figure 13: Profits generated in February, 2020[5]

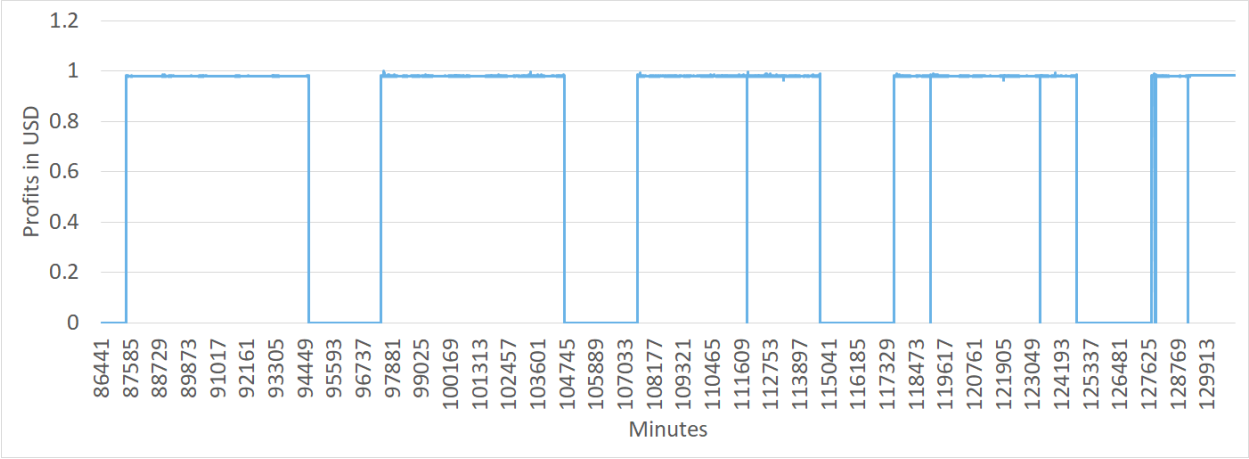
For March, as illustrated in Figure 14, both fiat and stablecoin strategies maintain the same level of profitability as observed in January and February. However, the pure cryptocurrency and mixed strategies result in extreme outcomes that would likely not have been practical trades to make given the ability to fulfill the trade orders. Indeed, as seen in Figure 15, the pure cryptocurrency

[5] The horizontal axis of the graphs denote the number of minutes that have been passed since 1st January, 2020, 00:00:00 AM.

strategy identified a population of arbitrage trades that has a distribution with 50% of profits getting as high as US$87,085. Under the mixed strategy, the median arbitrage profit identified was to the tune of US$342,345. The outliers for both strategies saw even more extreme profits ranging from US$350,000 to US$5 billion and US$1m to US$45 billion.

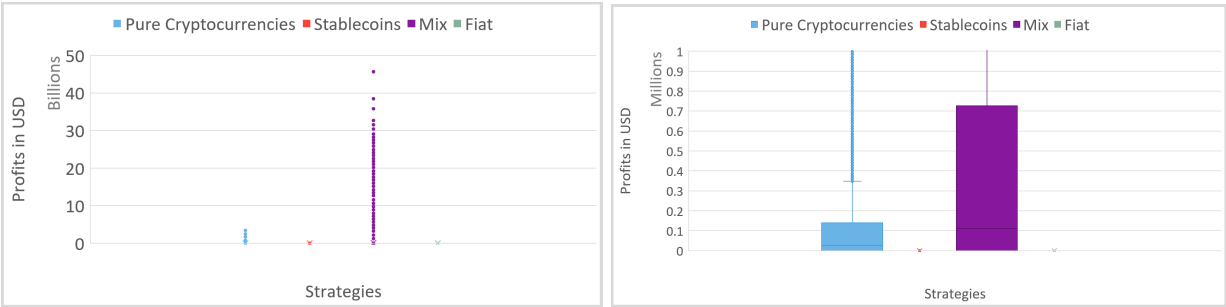


a) Stablecoins



b) Fiat currencies

Figure 14: Profits generated in March, 2020



a) Full graph **b) Zoomed in version**

Figure 15: Profits generated in March, 2020.

It is worth noting that while the pure cryptocurrency and mixed strategies do generate extreme and impractical trading outcomes in March of 2020, much of this arbitrage came at a point in mid-March 2020 when markets had become significantly more volatile as fears of an impending armageddon took hold of the global economy. Compounding this volatility was the credit crunch in capital markets as retail traders and institutional investors began facing unprecedented levels of margin calls and resulted in the selling off assets, including gold, in order to satisfy payment obligations. In the credit derivatives market for example, ICE Clear Credit alone during the onset of Covid-19 from February 24 2020 to March 27 2020 reported average daily payment obligations 9 times higher at US$1.3 billion, than the pre Covid-19 period levels of $148 million.

In fact, as illustrated in Figure 16, this period and by extension the arbitrage profits identified, was indicative of a cryptocurrency market transition between an on-risk environment to an off-risk environment and back to an on-risk environment as volatility subsided. This transition is also highlighted in the overlap in the spike in the 10-Year US Treasury price and the collapse in bitcoin and other cryptocurrency prices (Figure 17). Given that the 10-year Treasury yield is an indicator of broader investor confidence, the sharp drop in yields and associated jump in 10-year Treasury prices to a five year high points to the flight to safety of investors. By mid-May cryptocurrency prices recovered most of their losses as quantitative easing by the Federal Reserve and fiscal

expansion by the US Treasury saw the supply of treasuries increased by US$243 billion in May 2020 with further issuances in subsequent months depressing prices and keeping yields low.[6]

Figure 16: Bitcoin Price in USD (blue) vs Volatility S&P 500 Index (VIX), 2020.
Source: Tradeview

[6] See Onodi, K. (2020) "New US Treasury Issuance and Fed Purchases Impact on Indices in July 2020", Bloomberg Professional Services

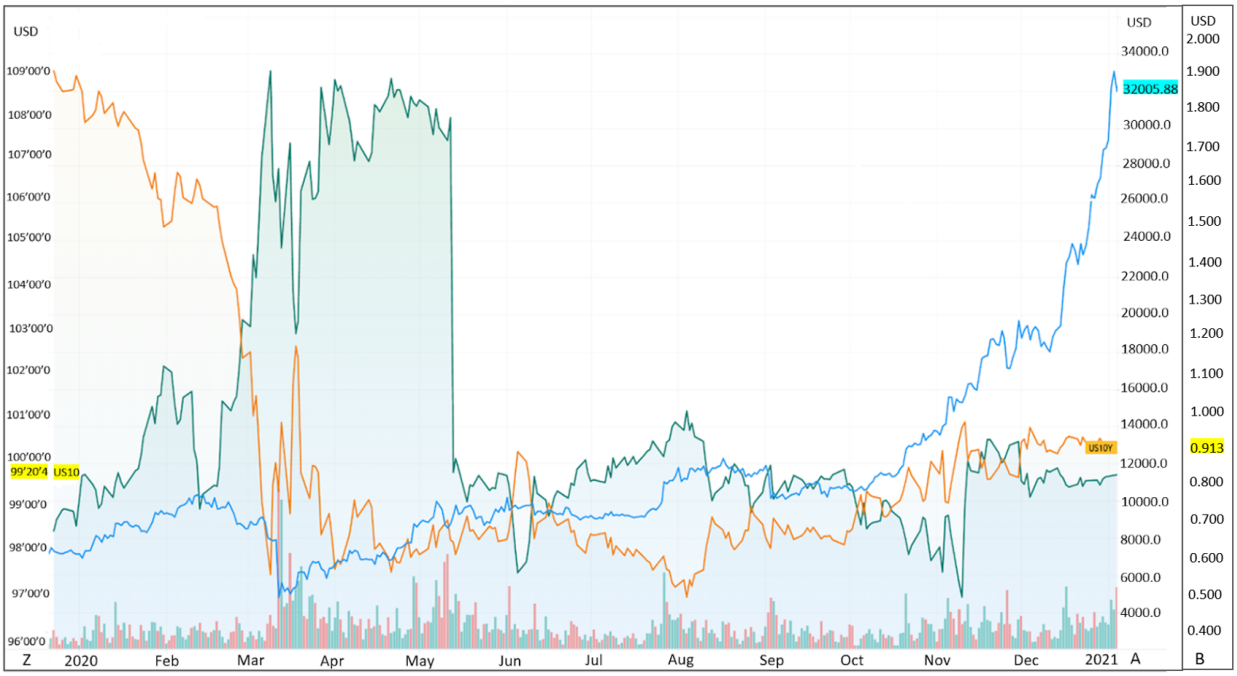


Figure 17: Bitcoin Price in USD (blue) vs US 10-year Treasury Price (green) and Yield (orange), 2020.
Source: Tradeview

3.3 Impact of Exchanges on Arbitrage

We further validate the results at exchange level from 10th May 2020 till 16th May 2020 to assess the extent to which available liquidity as measured by 24-hour trading volume impacts the attainable profits from the triangular arbitrage. At the exchange level, we run the arbitrage on all tradable currency pairs available in the CryptoCompare data; we focus only on exchanges that have a Coinmarketcap.com Exchange Rating above 5.0 and for which the USD is a tradable fiat currency. Arbitrage trading at exchange level can therefore be interpreted as the mixed strategy utilizing both pure cryptocurrencies and stablecoins from the previous sections. In the case of Binance and Gate.io we permit some currency risk since these exchanges require the purchase of USDT before any trading can occur. The summary data describing the exchanges is listed in Table 12.

Exchange	Exchange Score	24hr Volume	Number of cryptocurrencies	Number of Markets	Percentage of Possible Markets Tradable*

Binance	9.9	US$51,158,178,494	90	735	9.28% (0.95%)
Coinbase	8.6	US$4,958,376,192	26	46	7.36% (5.69%)
Kraken	8.5	US$3,081,205,476	35	100	8.65% (7.63%)
Gate.io	8.3	US$3,668,034,080	37	423	32.64% (0.30%)
BitFinex	8.1	US$2,124,247,235	118	389	2.84% (1.75%)
Gemini	7.3	US$525,478,010	6	15	60.00% (3.36%)
Bittrex	7.4	US$414,744,565	253	455	0.72% (0.60%)
Exmo	5.7	US$158,019,531	31	120	13.33% (4.92%)

Table 12:Exchange structure based on Cryptocompare Data
*** percentages in brackets reflect the listings reported by Coinmarketcap**

From the results, we observe that arbitrage profits achieved within one exchange is very limited as compared to the previous experiments where the trade between currencies was not limited to a single exchange. As illustrated in Figure 18, once limited to trading within Kraken, Binance or Coinbase, the number of tradable cryptocurrency pairs available relative to the 24-hour volume within these exchanges appear to play a role in the maximum attainable arbitrage profits. Across the top three exchanges, we observe only a maximum profit of roughly US$1.5 per trading minute over the period between 10th May 2020 and 16th May 2020. By contrast, within Bittrex, which is ranked twelfth on Coinmarketcap and has a higher ratio of tradable pairs to 24-hour trading volume, three quarters of the profits are between US$2 to US$3 and in some extreme cases we even see profits of more than US$6. Suggesting that trading activity on Bittrex is more prone to adding volatility to the broader cryptocurrency market. Moreover, a comparison of tradable markets to potentially tradable markets based on the number of cryptocurrencies available on the exchanges suggests that Bittrex is significantly more fragmented than Binance, Coinbase and Kraken.

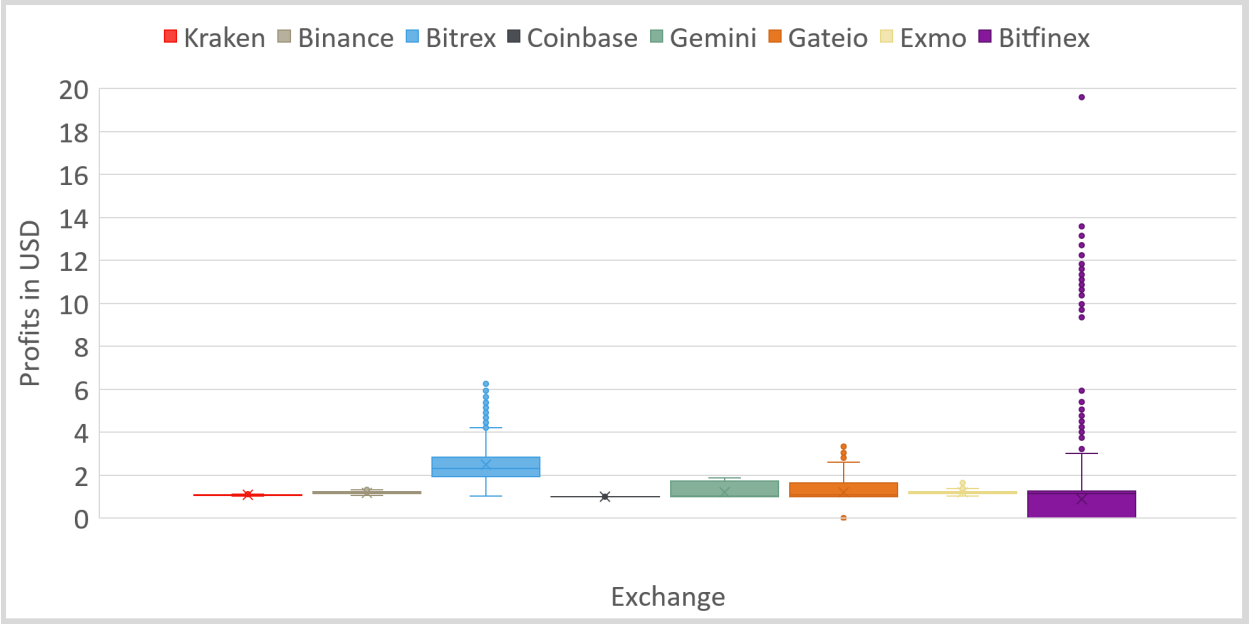
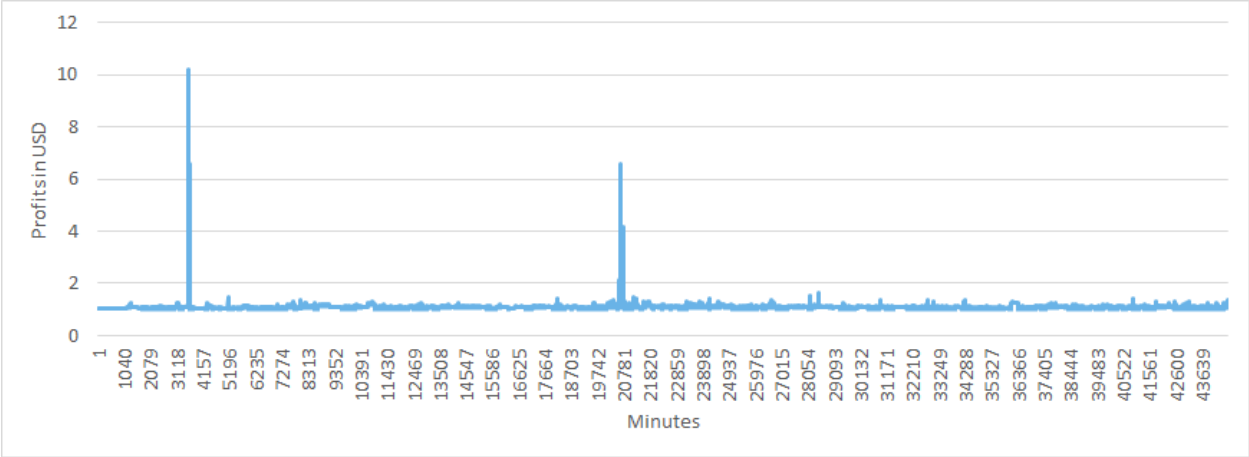


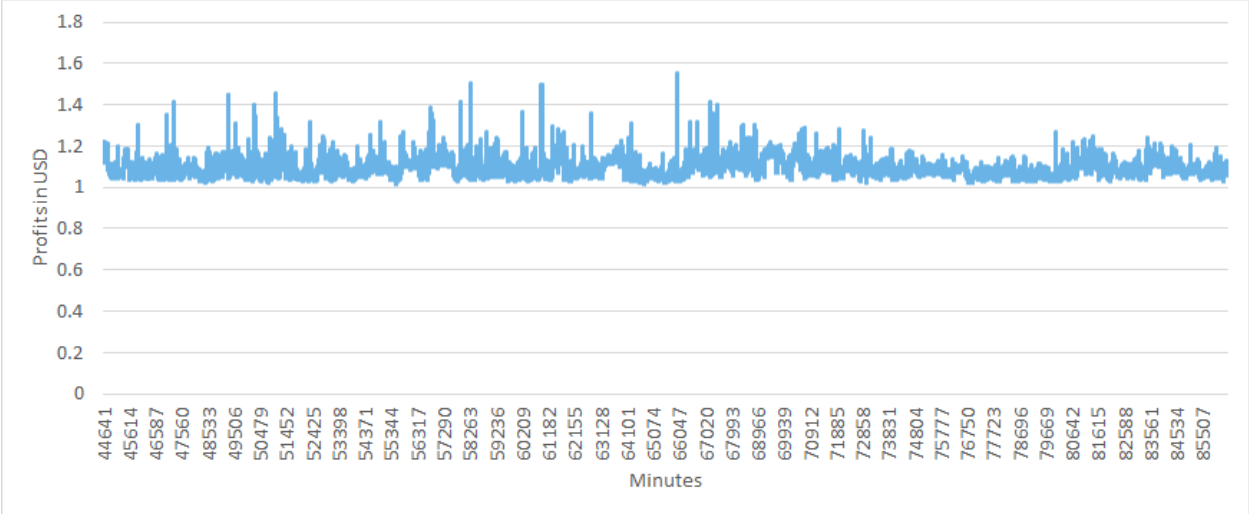
Figure 18: Boxplot comparison between profits in different exchanges.

Further investigation into the contribution of exchanges to broader market volatility is beyond the scope of the current analysis but may represent an important area for exploration; particularly going back to our analysis of arbitrage at the tail end of February and throughout March of 2020. By way of contrast to the global market level where we observed exploding triangular arbitrage trading profits in both the pure cryptocurrency and mixed strategies, we see much more realistic and stable returns on these strategies at the exchange level. Focusing on Kraken and trading the mixed strategy, we observe from Figure 19. (a) to 19. (c) that beyond a few outlier events that see profits hitting as much as US$10 on the US$1 outlay, profits consistently remained under US$2 for the entire January 2020 to March 2020 timeframe. Moreover, for a significant period of time towards the end of March the genetic algorithm was unable to find profit opportunities under the mixed strategy. This suggests that despite markets being somewhat inefficient in so far as profits are consistently attainable, the extreme volatility often ascribed to cryptocurrencies only exists

outside of the more established and liquid exchanges.[7] Consequently, policies fostering the maturing of exchanges may minimize this volatility risk.

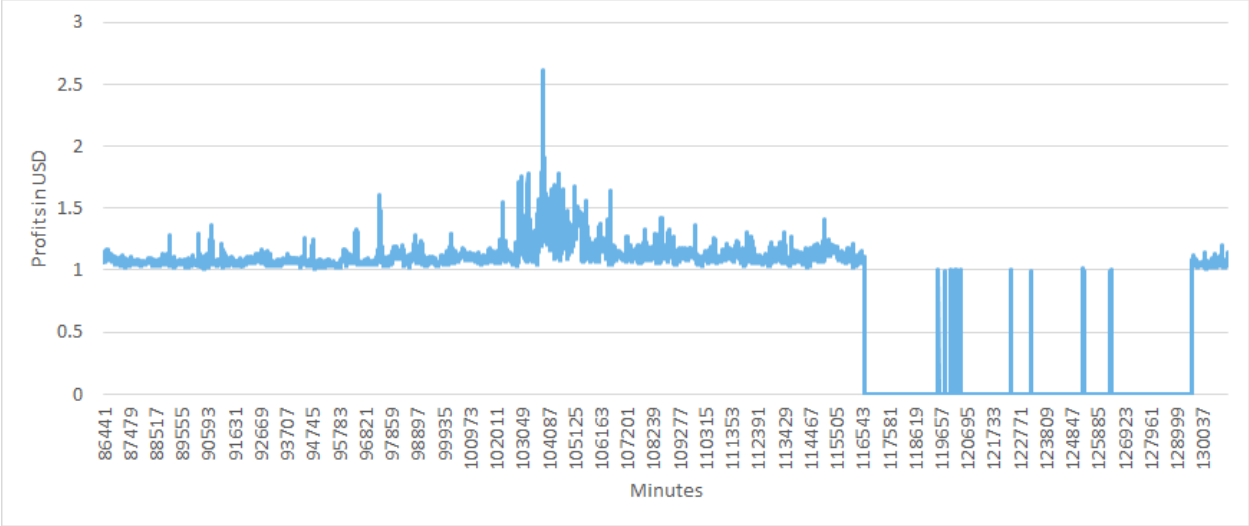


a)January 2020



[7] This is consistent with findings of Markov and Schoar (202) who show that there are larger arbitrage opportunities trading between exchanges exchangeshttps://www.sciencedirect.com/science/article/abs/pii/S0304405X19301746

b) February 2020



c) March 2020

Figure 19: Profits in Kraken from January till March 2020

4 Conclusion

This paper assessed the efficiency of cryptocurrency markets by determining the existence of persistent arbitrage profits using the triangular arbitrage FX trading strategies on high frequency data. More specifically, we employ a genetic algorithm based global search heuristic to identify optimal arbitrage trades across four core strategies (pure cryptocurrencies, stablecoins, mixed, and fiat). We compare the mean and the theoretical upper bounds of attainable profits across the four strategies over the three-month period between January and March 2020 and find profits to be consistent. As expected, triangular arbitrage trading yielded no arbitrage profits with the fiat currency strategy. With these digital currency strategies, however, we observed varying degrees of persistent tradable arbitrage profits, from $2 in the case of stablecoins to $5 and $25 in the case of the pure cryptocurrencies and stablecoins mix strategy respectively. Outside of the market dislocation in late February and March 2020 caused by broader market reactions to COVID-19, these profits remained fairly consistent. This would suggest that while markets for private digital currencies exhibit pricing inefficiencies, these inefficiencies may be part of ongoing price

discovery rather than inherent volatility present in these currencies. Moreover, even during the asset price crash of late February to mid-March 2020, arbitrage profits in the stablecoins strategy remained well pegged to fiat while the pure cryptocurrency and mixed strategies appear to have been impacted by the fundamentals of risky assets during on and off-risk environments. In other words, the collapse in cryptocurrency prices and exploding arbitrage profits were an indication of the heightened volatility caused by concerns over COVID-19 and the broader markets' flight to the USD and asset sell-off.

Further, we find that exchanges play a significant role in pricing misalignments and inefficiencies in the private digital currency market. While not exhaustive and requiring further research, our analysis of eight of the most liquid exchanges suggests that exchanges with higher market depth with respect to available currencies relative to actual tradable currency pairs appear to be those with better price alignment and lower and less volatility we observe in arbitrage profits. From a policy standpoint therefore, the monitoring of market depth may prove a useful tool in developing better oversight frameworks or regulatory sandboxes for exchanges as more sophisticated traders enter into cryptocurrency markets.

It is worth recalling that not only does our selection of the optimal chromosome length focus on the upper bound of profits, it does not seek explicitly to minimize the volatility. However, for the objectives of this research, this was appropriate as our focus was on identifying the lower and upper limits of profitability and the resulting volatility. In further research, we would impose further constraints of the genetic algorithm's global search by permitting only trades that would be consistent with orderbook limits across the various exchanges. Constraining the optimal trades to the orderbook limitations is important because as noted, the off-risk environment in March of 2020 would have meant that the trades generating the exploding profits were likely not possible due to the amount of liquidity required in the exchanges and time required to execute such trades. Indeed a production deployment of our genetic algorithm on a trading desk would, among other things, consider the risk adjusted profits rather than nominal profits. Such a production deployment would also be constrained by the size of orders that could be put through at any moment in time. Nevertheless, the insights our current research provides with respect to the alignment of stablecoins to fiat even at the height of the off-risk environment has meaningful policy implications as to the underlying management of stablecoins by their issuers.

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6 Appendix

Appendix 1. List of pure cryptocurrencies

ADA - Cardano
ALGO - Algorand
BCD - Bitcoin Diamond
BCN - Bytecoin
BCH - Bitcoin Cash
BSV - Bitcoin SV

BTC - Bitcoin
BTG - Bitcoin Gold
DASH - Dash
DCR - Decred
DGB - DigiByte
DOGE - Dogecoin
ETC - Ethereum
ETH - Ethereum
HC - HyperCash
HOT - Holochain
IOST - ISOT
LSK - Lisk
LTC - Litecoin
MIOTA - Miota
NANO - Nano
NEO - Neo
NPXS - Pundi X
QNT - Quant
QTUM - Qtum
RVN - Ravencoin
THETA - Theta
TRX - Tron
XMR - Monero
XVG - Verge
ZEC - Zcash

Appendix 2. List of stablecoins

ABBC - ABBC coin
ATOM - Cosmos
BGBP - Binance GBP
BITUSD - BitUSD
BTS - BitShares
BUSD - Binance USD
DAI - Dai
DENT - Dent
EURS - Euros

GUSD - Gemini dollar
MKR - Maker
OMG - OmiseGo
PAX - Paxos
STEEM - Steem
TUSD - TrueUSD
USDC - USD Coin
USDT - Tether
VET - VeChain
XEM - Xem
XLM - Stellar
XRP - Ripple
XTZ - Tezos

Appendix 3. List of fiat currencies

AUD - Australian Dollar
CAD - Canadian Dollar
CHF - Swiss Franc
CZK - Czech Koruna
DKK - Danish Krone
EUR - Euro
GBP - British Pound Sterling
HKD - Hong Kong Dollar
HUF - Hungarian Forint
JPY - Japanese Yen
MXN - Mexican Peso
NOK - Norwegian Kroner
NZD - New Zealand Dollar
PLN - Polish Zloty
SEK - Swedish Krona
SGD - Singapore Dollar
TRY - Turkish Lira
USD - US Dollars
ZAR - South African Rand