Volatile Derivatives: Using Monte Carlo Simulations to Assess Profitability of an Adaptive Trading Strategy

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Abstract

The emerging field of cryptocurrencies and their related financial derivatives have received considerable attention in recent years. Cryptocurrencies or *'crypto'* has made fortunes for many, and bankrupted others. As of November 2018 there are approximately 2000 cryptocurrencies in circulation [2], but they are all shadowed by Bitcoin in reputation, and trading volume. Bitcoin was developed by the anonymous Satoshi Nakomoto and released in 2009. Bitcoin aims to serve as an electronic peer-to-peer, decentralized monetary system. The following exceprt is form the Bitcoin Whitepaper:

> *"A purely peer-to-peer version of electronic cash would allow online payments to be sent directly from one party to another without going through a financial institution. Digital signatures provide part of the solution, but the main benefits are lost if a trusted third party is still required to prevent double-spending. We propose a solution to the double-spending problem using a peer-to-peer network. The network timestamps transactions by hashing them into an ongoing chain of hash-based proof-of-work, forming a record that cannot be changed without redoing the proof-of-work. The longest chain not only serves as proof of the sequence of events witnessed, but proof that it came from the largest pool of CPU power. As long as a majority of CPU power is controlled by nodes that are not cooperating to attack the network, they'll generate the longest chain and outpace attackers. The network itself requires minimal structure. Messages are broadcast on a best effort basis, and nodes can leave and rejoin the network at will, accepting the longest proof-of-work chain as proof of what happened while they were gone."* - [1]

Despite the revolutionary technologies and ideas that crypto has introduced, the field from a financial perspective is speculative and highly volatile. On November 23, 2016, Bitcoin was trading at \$743, on December 17th, 2017, it was trading at \$19,437, and on November 25, 2018, it was trading at \$3770.

This project explores the profitability of an adaptive trading strategy in these volatile markets. The derivative studied is the XBTUSD perpetual swap as offered by Bitmex.com. The choice of XBTUSD was motivated by the fact that it is highly liquid, as well as the fact that Bitmex offers margin trading on XBTUSD with up to 100x leverage, which provides opportunities for greater profits at significantly higher risk than those in spot markets. The combination of high liquidity, high leverage, and high volatilility make trading Bitmex's XBTUSD comparable to casino games. This project investigates the potential edge of a specific trading strategy through Monte Carlo simulations.

Preface

Bitmex and the Perpetual Swap

Bitmex, founded in 2014, is a cryptocurrency derivatives trading platform, and the subject of significant controversy with regards to regulations and markt manipulation. Despite the controversies, however, Bitmex accounts for several billion dollars worth of crypto-derivatives traded *daily* – a volume comparable to that of the stock market.

Bitmex is best known for its "Perpetual Swap", *XBTUSD*, which is similar to a traditional futures contract and has Bitcoin as the underlying asset. However, it differs from a tradional futures contract in that

1. it never expires,
2. its price mimics the spot market price, and
3. profits and losses are settled in the underlying (i.e. calculated in dollars but settled in bitcoin)

Furthermore, Bitmex offers the use of *leverage* for trading XBTUSD on their platform. Leverage on Bitmex differs from leverage in traditional financial markets. Leverage on Bitmex is adjustable (1x-100x). Use of leverage allows the trader to take larger positions than their account balance – this leads to larger profits if the price moves in the direction favouring the trader, and larger losses and faster liquidation if the price moves against the direction favouring the trader. Bitmex's leverage feature is best demonstrated with a simple example:

Suppose Joe has \$1000 worth of bitcoin on his Bitmex account, then joe can open a trade worth \$2000 using 2x leverage. Furthermore, suppose that the current price of Bitcoin is \$3000; if Joe enters a long position worth \$2000 at 2x leverage and immediately Bitcoin's price goes up by %50 to \$4500, then Joe's profits are $2000 \times 0.5 = 1000$ meaning Joe has doubled his account. Similarly, if the price goes down by %50 to \$1500, then Joe's losses are $2000 \times -0.5 = -1000$ and since his starting balance was \$1000, Joe is now liquidated. The reverse would apply if Joe had entered a short with everything else in the example held constant.

Note that this is a simplified example. In reality, Joe's profits would be smaller, and his account would be liquidated before the price reaches the \$1500 (if he is long, and \$4500 if he is short). This discrepancy is due to trading fees, as well as XBTUSD's unique profit/loss calculations and settlement mechanism (i.e. profit/loss is calculated in USD, but settled in bitcoin). The detailes of these subtleties are omitted from the paper but are taken into account in the Monte Carlo simulations that follow.

The Strategy

The strategy consists of three parts: (i) Signal Generation, (ii) Risk Management, and (iii) Adaptation

(i) Signal Generation

At any given point in time the trade *signal* is one of three: (1) *Long*, (2) *Short*, or (3) *Flat*.

Long indicates a reasonable likelihood that the price will go up. When a long is signalled, we *buy* the derivative. *Short* indicates a reasonable likelihood that the price will go down. When a short is signalled, we *sell* the derivative. *Flat* indicates ambiguity regarding the diretion of price movement. When a flat is signalled, we close any open positions.

Two simple moving averages (notated as *MA* henceforth) of price lie at the heart of the signal generation system: a *slow* one, i.e. a longer period, and a *fast* one, i.e. a shorter period.

If the slow MA is beneath the fast MA and the price, then a *long* is signalled. If the slow MA is above the fast MA and the price, then a *short* is signalled. All other configurations of long/short MA's and price give a *flat* signal.

(ii) Risk Management

Risk is managed by use of *Stop Loss* orders and appropriate position sizing. A stoploss order protects the account from complete liquidation if the price were to move against the anticpated direction, (i.e. if the a long is opened and the price moves down, or if a short is opened and the price moves up). More intuitively, a stop loss order is placed at the price level beyond which we accept that we were wrong about the direction of price movement when we took the trade – 'beyond' means above if we are short, and below if we are long.

For every trade, a stoploss order is placed at the level of the slow MA. Furthermore, the size of each trade ('position size') is calculated so that only a fixed fraction of the account's equity is lost if the stoploss order is triggered.

Position size, α is calculated is a function of 1. $r =$*risk tolerance*: the fixed percentage of our account's equity which we are willing to risk losing on each trade. 2. p_e=*entry price*, 3. $C =$ *Capital* (in dollars), and 4. $s =$ *stoploss price level*: this is equal to the slow moving MA.

Let W be the dollar amount we are willing to lose on a trade. And let δ be the percentage change in price if the stop loss is triggered. Then $W = rC$ and $\delta = (s - p_e)/p_e$, and $\alpha = W/\delta$.

Note that $\alpha < 0$ if we are going short, and $\alpha > 0$ if we are going long. Also note that if $|p_e - s|$ is small, then α is big, and if $|p_e - s|$ is small enough, then α may be larger than the account's balance – this is the only scenario in which we use leverage. Leverage, $\mathcal{L} = \min(\alpha/B, \mathcal{L}_{\max})$ where B is the account balance in dollars, and $\mathcal{L}_{\max} \in (1, 100)$ is some predetermined constant – i.e. the maximum leverage we are not willing to exceed.

In our study we hold $\mathcal{L}_{\max} = 30$ and $r = 0.08$ constant. The optimal choice of r would make for an interesting subject for another Monte Carlo study.

Our strategy is built on the notion that by clever use of leverage, position sizing, and stoplosses it is possible to have an edge in Bitmex's XBTUSD markets.

(iii) Adaptation

The strategy *adapts* to changing market conditions by periodically reoptimizing the slow and fast MA period lengths to yield maximum profits.

Let S_p be the slow MA period length, and F_p be the fast moving MA period length. Furthermore let $Train_p$ be the *training period*: the number of price points on which F_p and S_p are optimized for maximum profit yield, and let $Test_p$ be the *test period*: the number of price points on which the optimal values of F_p and S_p are tested for profitability.

Our strategy starts at time=0 and conducts a gird search over $F_p \in [5, 15]$ and $S_p \in [20, 30]$ on from time=0 to time=$Train_p$ to get optimal values F_p^* and S_p^* which maximize profits from time=0 to time=$Train_p$. Then F_p^* and S_p^* are used to calculate percentage growth from time=$Train_p$ to time=$Train_p + Test_p$ and this percentage growth is recorded.

Then the above is repeated with time shifted right by $Test_p$ and the percentage growth is again recorded.

This procedure is repeated until the end of the data points is reached. Then all percentage growth values are multiplied and the value is recorded as the overall growth of the strategy on that particular price path.

In our study, we fix $Train_p = 200$ and $Test_p = 100$. These values were chosen so to not be too computationally intensive while still being reasonably adaptive. Optimal choices of $Train_p = 200$ and $Test_p = 100$ would make for an interesting subject for another Monte Carlo study.

Our strategy may be summerzied as a "Double Simple Moving Average Strategy with Rolling Opitmization, and Fixed Fractional Risk".

For the remainer of of this paper, we will notate the strategy as $\boldsymbol{Z}$.

Monte Carlo Simulations

The objective of this project is to estimate the expected growth of $\boldsymbol{Z}$ on the XBTUSD market. We can symbolize this objective as follows:

Let $\mathcal{P}^T$ be the set of all possible price paths for XBTUSD of length T. And let $\mathcal{P}_i^T \in \mathcal{P}^T$

$B(\mathcal{P}_i^T) = B(\mathcal{P}_i^T | B_0)$ be the account balance if every trade that $\boldsymbol{Z}$ suggested was taken, given some initial balance B_0. Let $\mathcal{Z} : \mathcal{P}^T \to (0, \infty)$, with $\mathcal{Z}(\mathcal{P}_i^T) = \frac{B(\mathcal{P}_i^T)}{B_0}$.

We are interested in calculating

$$\mathbb{E}[\mathcal{Z}(\mathcal{P}^T)]$$

However, due to the heavily path-dependent nature of $B(\mathcal{P}^T)$, this quantity is impossible to calculate analytically, but it can be estimated by

$$\mathbb{E}[\mathcal{Z}(\mathcal{P}^T)] \approx \frac{1}{M} \sum_{i=1}^{M} \mathcal{Z}(\mathcal{P}_i^T)$$

For some reasonably large M.

We use Monte Carlo to simulate price paths, $\mathcal{P}_i^T$, $i = 1, ..., M$ that mimic actual XBTUSD prices, and then calculate $\frac{1}{M} \sum_{i=1}^{M} \mathcal{Z}(\mathcal{P}_i^T)$

We fixed $M = 1000$, $T = 1000$, and $B_0 = 1000$, and used a geometric brownian motion as discussed in the STA3431 lecture notes to simulate price paths as follows:

Let S_t be the XBTUSD simulated price at time t. Start with $S_0 = 3770$ (price of XBTUSD on Sunday, November 25, 2018) and let

$$S_{i+1} \sim \mathcal{N}\Big(S_i + bS_i h, \sigma^2 S_i^2 h\Big)$$

where b, h, and σ are estimated using historical XBTUSD price data.

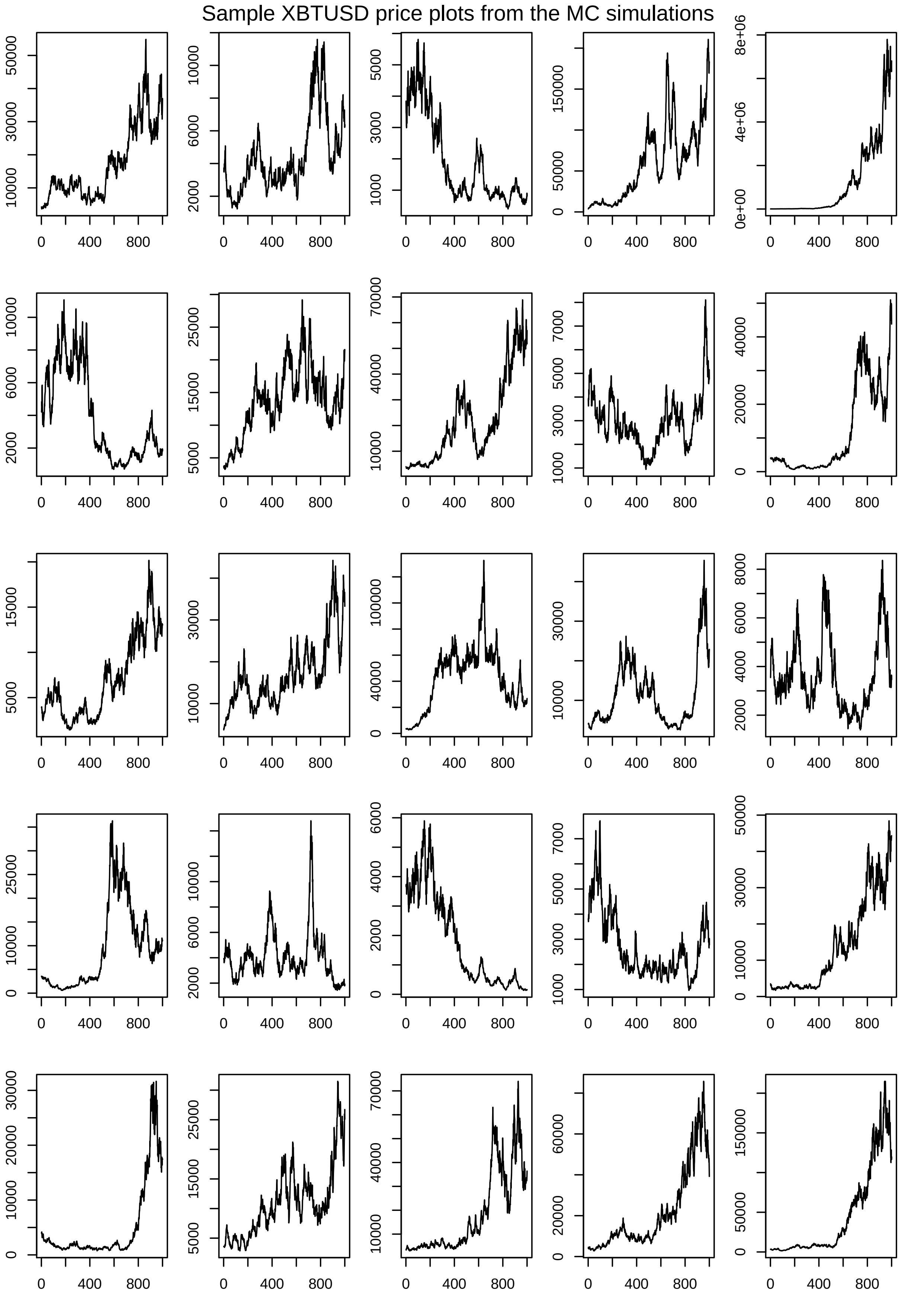
Let X_i , $i = 1, ..., T = 1000$ be the closing XBTUSD from the past 1000 days (i.e. X_T is the price on on November 25, 2018). Then we set $h = 1/365$ since there are 365 trading days (XBTUSD is traded 24/7), and use the maximum likelihood estimates for b and σ [3]

$b = \frac{1}{T-1} \sum_{i=1}^{M} \log\big(X_{i+1}/X_i\big)/h$

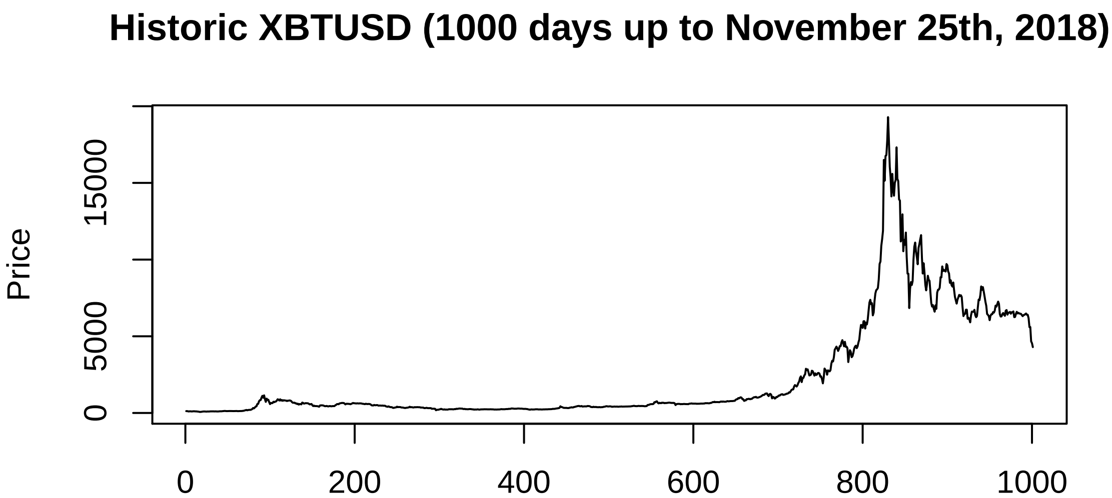
$\sigma = \sqrt{S^2\big(\{\log(X_{i+1}/X_i) : i = 1, ..., T-2\}\big)/h}$, where S^2 is the sample standard deviation.

We get $\hat{b} = 1.299824$, and $\hat{\sigma} = 1.178143$

The following are sample plots from the simulations:


Sample XBTUSD price plots from the MC simulations
0
400
800

And the following plot shows the actual XBTUSD prices:

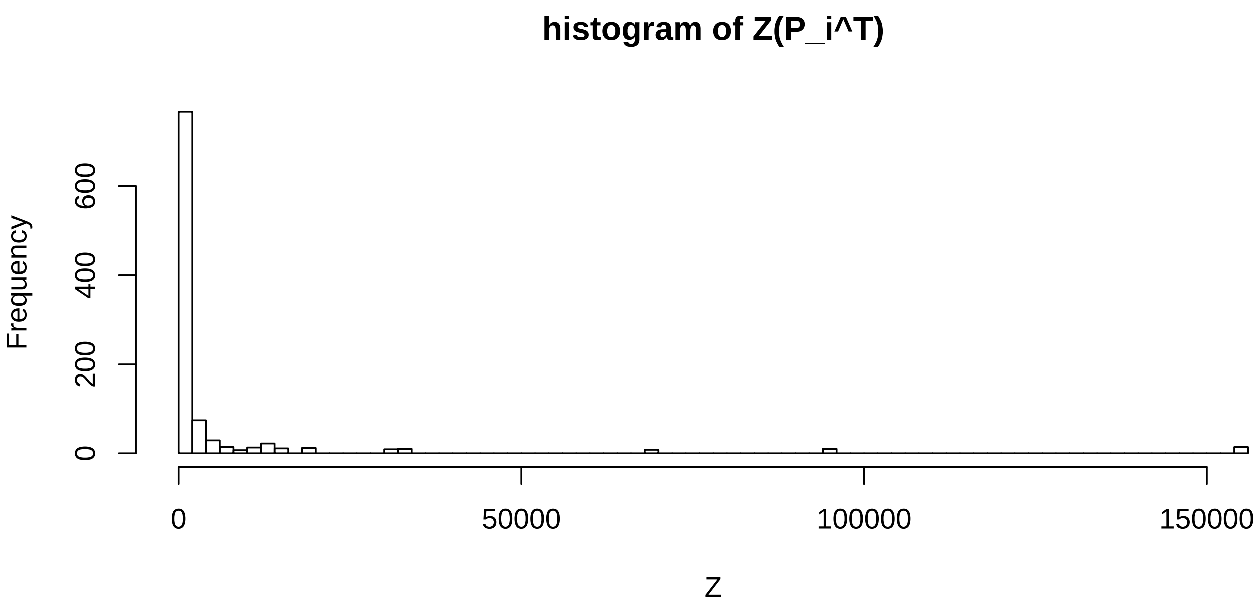


Results and Analysis

We found the mean of the M=1000 simulations to be 5837.095 with standard deviation 21664.94.

Using the same strategy on actual XBTUSD prices for the past 1000 days gave a growth factor of approximately 40, which is significantly smaller than 5837.095.

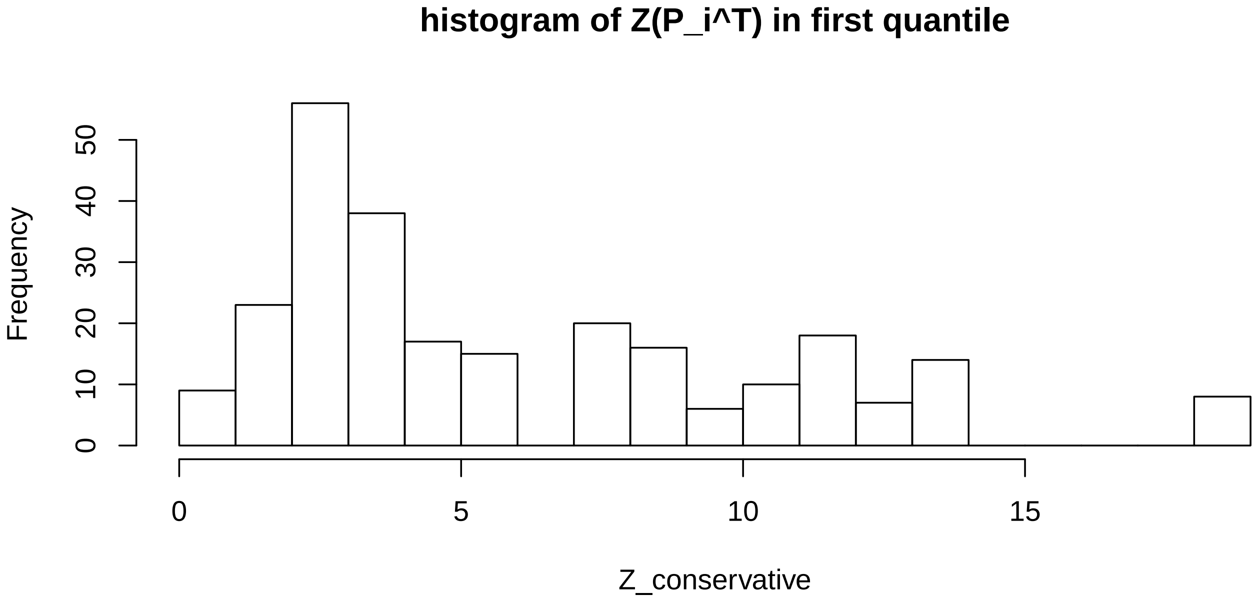
And furthermore, the standard deviation is huge in relation to the estimate, and so the estimate may be inaccurate. Also, the distribution is highly skewed, and the mean is inflated by few outliers. This is confimed by the histogram below.



But remarkably, less than 1% of the simulations were non-profitable, and %80 grew by a factor greater than 10!

To get a more conservative estimate of the expected growth, we will restrict our attention to the simulations in the first quantile:

Looking at the results in the first quantile, we have a mean of 6.052712 and standard devation of 4.483641. Growth by a factor is 6 over one thousand days is less impressive than 5837.095 but still impressive.



Of the conservative estimates, less than %4 were non-profitable, and more than %65 grew by a factor greater than 3.

We can be reasonably certain that the strategy has a high probability of being profitable *given that the actual XBTUSD price follows a Geometric Brownian Motion.* However, more simulations are needed to confirm this conclusion before taking out a bank loan for a Bitmex deposit.

Appendix

[1] Satoshi Nakomoto: "Bitcoin: A Peer-to-Peer Electronic Cash System", https://bitcoin.org/bitcoin.pdf

[2] coinmarketcap.com

[3] Course Notes for "Computer Intensive Methods For Stochastic Models in Finance", STAT 906, FALL 2005, as taught by Don L. Mcleish http://sas.uwaterloo.ca/~dlmcleis/s906/chapt7.pdf, page 379