General assessment of financial viability of Cogito coins

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Abstract

We create a financial simulation of the Cogito protocol. We use conservative assumptions to test how well our model performs in challenging situations. We demonstrate that we can offer our depositors substantial deposit rewards, in addition to a 1.2% average yearly token appreciation (albeit with the possiblity of considerable volatility). In a large scale simulation, we show that we can expect to have stable financials, with a low probability of holding bad financials (less than 1% of cases in 5 years of simulation had our internal metric CAR (defined in our whitepaper [Pus22]) under 50%). We also made a Monte Carlo simulation of a riskier investment strategy, which showed that we can also offer 2% index returns annually with reasonably low risk of hitting problematic levels of CAR. As such our protocol offers very low returns and is financially stable in the long run.

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1 Introduction

The cryptocurrency market is known for its large price swings. According to [Sma19], Bitcoin is one of the most volatile assets out there. Many other cryptpocurrencies share Bitcoin's high volatility and some are even more volatile. Crypocurrencies attract a lot of investors including those who wish to get rich quick as well as those who believe in the technological advancements. In general, investors in cryptocurrencies are usually used to price swings. However, since cryptocurrencies appeared, many different products also appeared. While most cryptocurrencies are very volatile, there appeared a need for more stable cryptocurrencies with lower volatility. The most used such products are the so-called stablecoins, which peg their value to another asset (usually American dollar) and keep the value on the exchanges the same as the value of the underlying asset to which they are pegged. They can then be used for transactions or also in smart contract creation. In the field of DeFi (decentralized finance [Rak22]), they help with many different applications. Decentralized finance (DeFi) offers financial instruments without relying on intermediaries such as brokerages, exchanges, or banks by using smart contracts on a blockchain. Stablecoins are therefore considered a safe investment among the cryptocurrencies. However, they are not perfectly safe - it did happen before [hea22] that they broke their peg and investors lost a big share of their money. A big part of the risk comes from the fact that they had been, up to the time of this writing, poorly regulated or even unregulated.

Over time, different types of stablecoins emerged. They can be fiat-backed, meaning that they are backed by traditional fiat currencies, that are (usually) established by government regulation and are often declared as legal tender. An example of that would be American dollar. But stablecoins can be also "crypto-backed", that is over-collateralized by another cryptocurrency to account for volatility, or "commodity-backed", usually backed by an underlying commodity, such as gold. Finally, there are algorithmic stablecoins, that have an algorithm that automatically expands or contracts the number of tokens in circulation in order to meet a specific price target. They all try to ensure stability and a peg to the underlying asset.

We propose a new type of stablecoin that tracks development indices instead of specific assets. Instead of enforcing hard pegs to the indices, we will try to maintain close proximity to them. We classify our protocol as low risk rather than as risk-free. This is a difference from most of other coins, which are either a high risk or they claim to be hard pegged to an asset that is not considered risky. Our coin therefore follows an index that should in the long run appreciate in value compared to other assets, such as fiat currencies.

We also implement a so-called deposit pool. There, the users can invest their money for a specific duration of time and gain interest on it. In our system that is better described in our whitepaper ([Pus22]), we ensure the stability and growth of our system by having this addition to the system. Users are incentivized to invest in a deposit pool in order to gain an interest on our tokens. This creates a complicated system, that offers users a pool of investment decisions and a relative stability. We can lose the peg to our index for a short period of time, but we do try to keep it, if only our financial situation allows.

In this paper we closely analyze the financial situation. We model the complexities of our protocol with investment of our capital in staking pools and other assets, so it appreciates and allows for positive index returns that we expect to have in the long run. It also invests a portion of our assets in deposit pool, to ensure the appreciation of a deposit to our depositors. Furthermore, we also keep a liquid reserve, which we use to ensure the peg of our coin to the index. We follow a variety of parameters in forms of stochastic processes to track our collateral, assets under management, deposit pool, tokens in circulation and other data that is financially relevant to our stability and protocol. We use a stochastic Monte Carlo simulation, where we simulate a complex system of index growth, investments, liquidity, users and investors behavior that influence the stability of a system that we proposed. In this paper we explain the methodology that we use, assumptions that we make and logic behind our simulation. In the end we also analyze the results of Monte Carlo simulation that we made of this system.

This paper is organized as follows. In the section of index simulation, we make simulations of the index. This is roughly the expectation of how our index will move in our simulation. In the financial returns section, we model the returns and risks of the investments that we take. In growth part, we simulate the growth of our system by comparing it to the growth of some stablecoins. While we are not a stablecoin, we do use them as an example of low risk investments, where we also belong. In the section that describes our strategy, we explain how the mathematical formulation of the whole system works as well as how we manage money each time that we rebalance the assets in order to ensure the stability of our coin as well as the future returns. All those sections make a stochastic simulation on an hourly basis over the period of 5 years in the future. We believe that this is the upper boundary of most investors in a fast growing and changing crytpocurrency market. So, we give a good overview of the risks in that period. Lastly, in the results section we make a single path and Monte Carlo simulation of the whole system as well as growth and investments and see how we perform. We then analyze the results and assess the general viability of our setup.

Our assumptions are described in the next sections, but some of the underlying assumptions of the financial model are: Rationality of the investors (if there is an investment with low risk that offers equal or higher returns than the similar one with higher risk, investors will always choose the lower risk investment). Investors have equal information about the market, markets are random (market movements cannot be predicted) and unless specified otherwise in a specific modeling part, the returns are distributed by Student-t distribution. We use that because we wanted to include fat tails in our modeling. We also assume zero transaction costs. This means that we do not assume transaction costs when transfering money to deposit and staking pools.

2 Index simulation

The purpose of our index is to track the humanity's progress in a specific area. In that way, our index should appreciate slowly, but steadily against the dollar. That is if the humanity is making a progress in that area. For now we will focus on Green coin that we are planning to launch that would track environmental progress. Other coins will have a similar dynamic of tracking index, but we might expect different returns in the long run. There are quite some of the indexes out there already that track the environmental progress to at least some degree (for example MSCI low carbon indexes [Cap22]). One of the indexes calculated for tracking the environmental progress is the one by Adriano Soares Koshiyama, which can be found on Github [Adr22]. This index was created by looking at the different environment indicators provided by The World Bank [The21]. From that the author calculated yearly changing index for the environment. It tracks different evnironmental indicators, such as access to clean fuels, agricultural emitions, threatened bird species, CO2 emissions, renewable electric consumption, forest areas, water flooding, urbanisation and many other. While the index did track the progress of the environment, this is not the exact index that we will use. Our model will have updates more often than the model by Koshiyama. Furthermore, we will aim to set it as a less volatile index. We will use the indicators that are being regularly updated in predictable time intervals. The World bank data that is used in this calculations has different indices updated in different times. Furthermore, while we do not get the regular tracking of the data, we also lack quarterly or even shorter period data. Our planned index will change more often. Lastly, the Koshiyama's index was relatively volatile; we plan to use different methods to decrease volatility and make it somewhat more predictable. We still use Koshiyama's index in the background, but we did adjust it a little in this simulation.

The purpose of this section is not to create a desired index, but rather to ajdust the Koshiyama's index in order to better reflect our planned index. So, we took the interpolated data for the index that are there from year 1981 until 2016. We further decreased the volatility by taking a 9 year average for the index before the year of calculation (and put that calculation a weight of 0.8) and add to it the current year of index (and added the weight of 0.2 to the current year). In essence, while we put a weight of 20% on a current year, we put a weight of $0.8 * \frac{1}{9} \approx 9\%$ on previous years. This means that we put a higher weight on most recent data. This is how we could then calculate the index from the year 1990 until 2016. Also, while we took the data from Koshiyama for environmental index, we assume that any index will follow similar distribution and we will only change the returns. This is a simplification for financial model until we develop more exact indexes.

2.1 Finding the statistical distribution behind our index

We want the index to update at least every 3 months, if not more often. This would better reflect our own index that we plan to design in the future as well.

So, we tried to look at the yearly changes and add 3 more values between each two years in order to get the quarterly data. But just linearly interpolating would underestimate the volatility that we go through every quarter with such an index. On the other hand, we unfortunately do not have the information about the real distribution of quarterly index updates. So, we decided to assume that between two years we have quarterly updates of the index where the expected growth is exactly the same one as it happened. Furthemore, quarterly updates are modeled using normal distribution, using a distribution of $N(i_t - i_{t-1}, stdy/2)$. Here, i_t is the index value at time t and $stdy/2$ is the standard deviation of yearly index changes. So, those distributions are used to fit the quarterly data. This is not a perfect solution, but we do add quarterly numbers, so we took an assumption that they change in the way that normal distrubtion reflects their changes. This is how we get (or approximate) quarterly data for our period from 1990 until 2016. We can calculate the differences in quarterly growth, to see how our growth was increasing. We then approximate the distribution of those differences using Python's Fitter package [Fit]. This package uses 80 distributions from Scipy and checks what is the most probable distribution and the best parameters. Due to our design, this is depending on what outputs the randomly generated numbers for quarterly data are, so we do save the random seed. In our case, we got Generealized normal distribution with parameters $(1.3018, 0.0013, 0.0207)$. Those parameters represent shape, location and scale respectively. For easier understanding we have rounded the parameters on 4 decimal points in this paper (but not in actual simulation). This is what we use to generate new indexes in the future.

However, while this gives us some idea of the volatility (though in our future index generation we will try to decrease it), we were not quite satisfied with the returns. The past data predicted around 0.5% appreciation per year. The drawback is that it used the data for the years when environment was not nearly as big topic as it is today. Today the countries invest substantially more in the improvement of the environment. This is why in the recent years the index components grow significantly faster and are predicted to grow faster in the future as well. So, for the green coin we instead decided to manually adjust the return. We will do the same for other coins, since this index is somewhat an approximation of our final planned index that we plan to use. Furthermore, while we are getting the data for Green coin, we are (in this paper) interested in the stability of the system given the returns more so than the actual index. So, we model possible returns for general index, not necessarily Green index and test the system's stability given the returns. We set the expected value parameter on 0.00298659 instead, because this nets us with a roughly 1.2% appreciation per year ($(1 + 0.00298659)^4 \approx 1.012$). We then generated 10,000 indexes for 20 periods in the future (5 years), to see our expected appreciation and possible lower and upper bound values.

We can see an example of a generated index in figure 2. We can see the average return in figure 1. It is around 6% in 5 years, just as we wanted. Last, but not least, we can see how the index appreciates and in what bounds it usually is at figure 3. We can see that in 5 years, we can expect the index

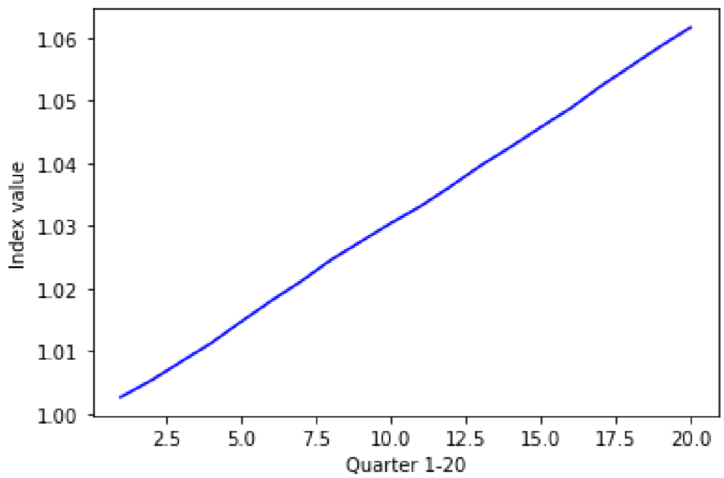

Figure 1: Average expected appreciation of our index (in 10,000 simulated runs)

appreciation from a starting value of 1 to between 0.88 and 1.25 in 2.5% and 97.5% confidence intervals.

We also make another index with 2% yearly appreciation and test a different investment strategy later on to see if we can offer even higher returns in a potential index. There we set a quarterly return parameter at 0.00496293, which should reach a roughly 2% yield after a year. Note that this might not be the enviromental index, but other potential indexes that we are planning to develop. This is a risk assesment on whether 2% return on such indexes is sustaiable.

2.2 Use in our simulation

Having created an index, we need to make a slight adjustment, so it can fit our simulation. That is that we do not use quarterly but hourly changes of the index. However, index is simulated on a quarterly level. So, we assume that we only set new values every quarter and then make hourly increases (or decreases) of price in the same increments, so that it reaches our simulated return in exactly 3 months time. So, if the return is x in the next three months, we make an increase every month for $x/(24*31*3)$ for the next three months of time.

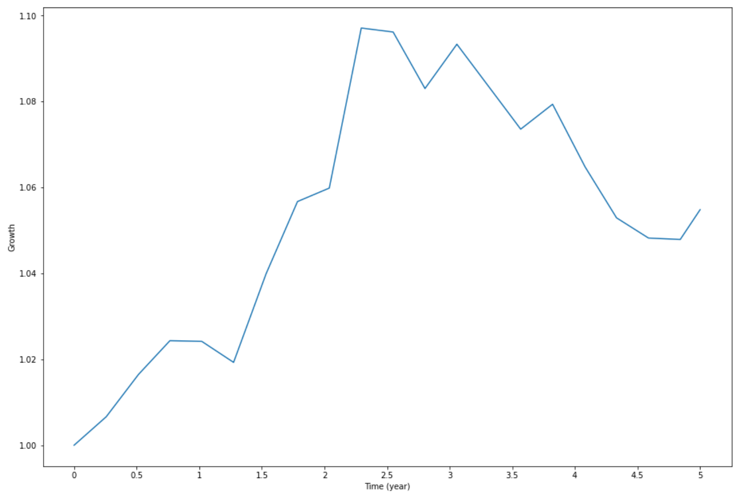

Figure 2: An example of a generated index

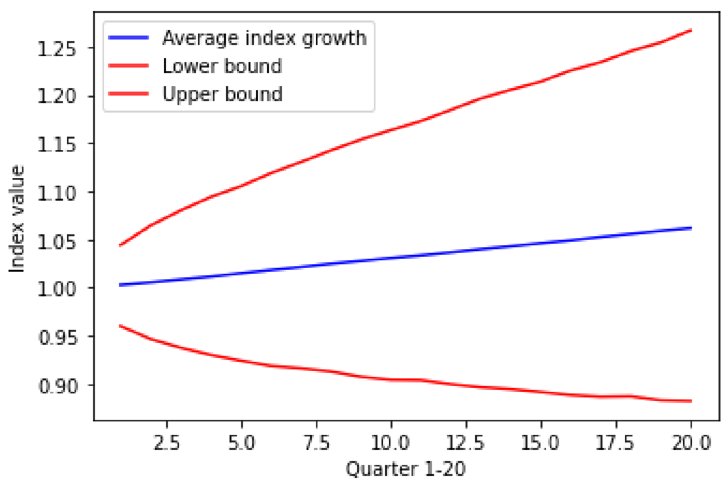

Figure 3: Simulation of 10,000 generated indexes together with lower and upper 97.5% confidence bounds (for 20 quarters in the future)

3 Estimating long term financial returns

In this simulation, we will assume that we invest all of our investments into the staking pools. The idea behind this is that they are reasonably safe investment with low returns. We do not need high returns (at least in this simulation) because our index does not appreciate very fast. So we decide to invest in staking pools in this simulation. But we are careful because it did happen before that staking pools defaulted or were hacked, so they are not without risks. The companies behind them can also default because of financial and operational reasons. We model those risks as described in this section.

3.1 An overview of some different staking options

3.1.1 Staking pools for proof-of-stake coins

Some of the coins have a so-called proof-of-stake algorithms. They work by selecting validators in proportion to their quantity of holdings in the associated cryptocurrency. This is an alternative to proof-of-work algorithms such as Bitcoin and uses much less computing power and with that - electricity and pollution. The issue here is that bigger players have a higher chance of confirming a transaction and in this way taking a higher proportion of a transaction fee. Stakers therefore aggregate together in big pools, which have a higher chance of confirming a transaction. They then split the transaction fee.

3.1.2 Staking pools for utilizing loans

On the financial markets (and in DEXs), people constantly take leveraged positions in different coins. So, there are pools which offer liquidity for borrowing, take a certain percentage of interest on the loan and then make a profit on that. They let other people deposit their coins and then use them forward for loaning onwards. They get a percentage of return from those loaned coins. It is a relatively low risk.

3.1.3 Yield farming

This is investing in the yield farming pools, which help manage your funds by using arbitrage on decentralized exchanges. It is risky and its future in uncertain, but it can earn good returns, if done right (and in the right conditions).

3.1.4 Staking pools that earn in different ways

There are other methods that we are constantly observing and assessing their viability.

3.2 Estimating returns and probability of negative events

3.2.1 Negative shocks

First we will focus on what we consider negative events. Recently many new platforms and protocols have emerged. Not all of them had good economics behind them. There is a need to constantly observe new projects and their viability. Some of them have promised substantial returns, however those were not sustainable in the long run and many of them went bankrupt. Furthermore, there have been a lot of hacks and protocol failures. In such cases, we might have invested money in those protocols and lost a portion or all of it. We should always account for that possibility. When such a thing happens, we are exposed to high losses in a very short amount of time. The good thing is that this seems to be a new industry. Since the industry is still emerging, we have much more unwanted events than we will have once it is more mature. So, the probability of such events is likely to go down. This is in line with prior work done by Oosthoek and Doer [Kri21], who have examined hacks in Bitcoin exchanges and found out that the frequency of hacks and the amounts stolen decrease with time. We expect similar movement with staking protocols. While we have a lot of them right now with weak security, we expect the security and the amount of hacks to decrease over time. We also expect to have more protocols with solid economics behind them, at least from those that we choose to invest. Furthermore, when holding and investing a stablecoin, we plan to use only those that are 100% backed by a stable collateral. A stable collateral is assumed to be other trustable stablecoins, low risk commercial papers or cash equivalents. We have made an analysis of failed (hacked) staking protocols, to assess how often we can expect to lose funds.

As seen in table 1, there were quite a lot of hacks that happened in the recent years, but most of them did not result in loss of assets for its clients. Even those who did were mostly smaller projects or badly collateralized coins. Since we only care about the loss of our invested funds when analyzing the returns, we can gather that the chance of that is pretty small. Most platforms did not lose significant amounts of investor's money. Furthermore, since we want to make a relatively safe coin, we plan to invest in lowest risk platforms with lowest probability of default and of being hacked. This gave us some guidelines at determining the probability of loss of funds in the invested protocol.

3.3 Expected returns of staking

Another topic that is important when estimating the future expected returns is the returns that we can expect from staking. In order to do that, we have followed several different approaches. There is a lack of reliable data regarding the historical returns from staking. This is besides the fact that staking has not existed for very long, so the whole history is quite short in the first place. We have got the data about historical returns for staked stablecoins from [Staa]. However, when we went to manually check today's values of those returns, we found significant deviations of returns compared to our price. This is partially

Table 1: Recent hacks in DeFi that resulted in a loss of $30 million or more

Platform	Stolen amount	Did users lose?	Source 1	Source 2	Importance
Ronin Network	624M	Probably	[Kor22]	[Newl]	Not relevant (different niche)
Poly Network	611M	NO	[Bro]	[Newk]	No loss of money
Wormhole	326M	NO	[Newn]	[Cur]	No direct relevance, no loss for us
Bitmart	196M	NO	[Newc]	[Sig]	Exchange, no loss of funds for us
Beanstalk	182M	YES	[Newb]	[Fai]	Questionable if we would invest there.
Compound	147M	NO	[Beh]	[Jag]	Relevant
Cream Finance	136M	No, but froze returns	[Uni]	[Newe]	Possibly relevant to us.
BadgerDAO	120M	YES	[Stab]	[Newa]	Not very relevant
Mirror protocol	90M	YES	[Tra]	[Newh]	It is on LUNA after LUNA failure. And has a history of hacks and exploits. So it is unlikely we would invest in this.
Fei Rari	80M	Unknown	[Greb]	[Finb]	Weak. Low marketcap
Qubit Finance	80M	YES	[Ade]	[Hop]	Slightly, a bit risky before hack
Ascendex	77.7M	NO	[Grea]	[Asc]	Somewhat
EasyFi	59M	Partial to 100% retribution	[Coi]	[Bit]	Not a strong relevance for now
Uranium Finance	57M	Unknown	[Newm]	[Fad]	Probably not relevant
bZx	55M	YES	[TFL]	[Newd]	A bit risky for us
Upbit	49M	No	[Roz]	[Joh]	Not likely
Cashio	48M	YES	[Qui]	[Mic]	Not relevant, gaming
PancakeBunny	45M	NO	[Newj]	[pan]	Yes
Kucoin	45M	NO	[Newg]	[Au]	Yes
Alpha Finance	37.5M	NO	[You]	[Tur]	Not very relevant
Vee Finance	34M	Probably not	[Insa]	[D]	Somewhat
Crypto.com	33.7M	NO	[Insb]	[Newf]	Yes
Meerkat Finance	32M	YES	[Cra]	[Per]	Not relevant (new, too risky platform)
MonoX	31.4M	Probably	[Goo]	[Newi]	Not relevant (new, too risky platform)
Spartan protocol	30.5M	Partially	[Spa]	[Imm]	Not very relevant
Grim Finance	30M	Partially	[Fina]	[Rep]	Not relevant (new, too risky platform)

because they often post the returns of coins paid out in native tokens, which is not something we are looking to do. It still gives us some idea about the current volatility of the returns, but unfortunately we did not get reliable data from there. In order to predict realistic staking returns in the long run, we have decided to make several assumptions. Firstly, we assume that staking is not risk free, so we do not get a return without a risk. And investors are rational. As such we can expect that investors will (in the long term) demand higher return on staking than they do in investing risk-free bonds. Of course, we also estimate the probability of default in our simulations. Furthermore, we do not expect a stable return throughout the time. Instead we expect it to vary based on the market conditions. For example, in bull market, people and institutions are likely to take higher risks and borrow more assets, allowing for a bigger return on staking. However, when the times are bad, we expect lower staking returns as well. Given that previous staking returns were highly volatile and many of them were driven by unsustainable business models, we cannot really take them as a perfect example. There might be other alternatives, similar to staking that will emerge as the time goes on. We will follow them, but so far in this paper we will focus on what is achievable at this moment already.We do see however that current staking returns are between 1.5% and 15%, however the risk behind the two is vastly different. It was also similar for the limited past returns that we have observed.

3.4 Our model

In this section we will present the model that we use to estimate the future returns. We use a stochastic model and predict future returns with time increment of 1 hour for 5 years forward. 5 years is a lot of time and big changes are expected to happen in that time in cryptocurrency. We believe that time frame alone is hard to accurately estimate alone. Anything further exposes us to too much randomness and uncertainty. Or in other words, for all we know, we might reach technological singularity in that time and any prediction will be impossible. We use financial modeling for that time in the future using stochastic equations.

3.4.1 Market time or market confidence

By looking at the historical returns of Bitcoin and other cryptocurrencies, we can clearly see that the asset is very volatile. According to Coinmarketcap, it went from \$130 in mid October 2013 to \$1130 in December of the same year. It was then gradually losing value until mid 2016 when its value was around \$220. However, then the price increased to a record high of 19,500 in December 2017. After that we have seen years of negative performance again until January 2019. It reached around \$3900 at that time. After that, it had a gradual increase of value over the next two or three years, reaching a height of around \$68,000 in November 2021. After that it has started decreasing in value again. And this was just Bitcoin. Other cryptocurrencies followed a similar pattern, although most of them had a higher volatility. Therefore, we model part of that, that is the market confidence and how it affects the staking market. The idea is that staking returns will be correlated with crypto market. But they will still have a significant part of the volatility that will be the property of staking alone.

Given the timeline we just described earlier, we can see that cryptocurrency market has the periods when it grows and retracts. By the eye one would be tempted to say that the periods of contraction and growth are of similar duration, however we do not have enough data to accurately assess this claim. However, based on this idea we model the general interest in crypto as a sinusoid function over time, which changes its run (negative or positive) roughly every 3 years.

Suppose $ltrstake_t$ be the state of the market in time t. $ltrstakevol$ is a constant that represents the volatility of the state of the market. This volatility does not change with time, however it adds another uncertainty because despite the market performance, we always allow for some volatility of a staking market, which can, especially in the short run react in its own way. Furthermore, let us take $markettime_t$ as current time in the market. That represents a time that runs over the course of our simulation. This is the time the way it is perceived by cryptocurrency market participants. For example, we might calculate that now it has been a certain amount since the top and that we are reaching the bottom. However, the market participants might not feel the same way. And this is what this process represents. We have:

$$ltrstake_t = sin((markettime_t/T) * \pi * 3) + ltrstakevol * W_t^1$$

Here T stands for the number of all the time points in the 5 years, so it is a discount factor. Note that volatility in cryptocurrency often comes in big unexpected jumps, so the normal distribution of volatility is questionable. Instead we want to include fat tails in our distribution. Therefore, we take Student-t distribution with 30 degrees of freedom for W_t^1 instead of normal distribution. This means that the tails are not very fat, however, it still allows for high extreme values and jumps.

While this already adds a movement of expected returns and adds volatility, we also want to make sure that in every simulation the market time and with that periods of growth and retraction are perceived differently. So we define a process:

$$dmarkettime_t = 1 + \sigma_{mkttime} * W2_t$$

Here we make sure that in the expectation market time is the same as our actual market, however we add a very volatile parameter $W2_t$, which has Student-t distribution with 1.5 degrees of freedom, making it very volatile with very fat tails. Here we want to model the behavior of market participants as more volatile with possible big jumps in their sentiment, that can happen because of the variety of news or other events. Furthermore, we set $markettime_0$ in such a way that it will represent the b in our calculations in order to not have a sudden jump to long term average. So, we calculate the starting market time by the b_0 that we are starting with. Also, dt in this case represents a movement by 1 hour time.

3.4.2 Staking rate

Staking rate is modeled using the following model:

$$dr_t = a_1(b_t - r_t)dt + \sigma_r * \sqrt{r_t} dW3_t$$

$$db_t = a_2(lbound_b + 0.01 * diff_b * (1 + ltrstake_t)) - b_t)dt + \sigma_b * \sqrt(b_t) * dW4_t$$

This is similar to Chen model, except that we use a two-factor model, because we do not model volatility as a process. The reason behind this is that we do not have a long enough history of how the volatility has changed, so we take a constant instead. Here r_t is our staking return. a_1 is the speed of reversion of the model, that holds the same purpose as speed of reversion parameter in Vasicek model. b_t here is a "long term mean level" of return that is a process by itself. σ_r is the "instantaneous volatility", which measures instant by instant the amplitude of randomness entering the system. Furthermore a_2 is the speed of reversion in the long term mean. $lbound_b$ is the lower bound of the b_t parameter. Due to volatility we can in short term go below that bound, but we expect to not hold the returns under it for long. The logic behind it is that investors will not accept the returns below a certain value that they could get elsewhere -

they will demand to be retributted for the risk they are taking. This only holds in the long run, but in the short run it can very well happen that investors are happy to have a return below that. $diff_b$ is the difference between minimum and maximum value of b_t (the long term one, not the actual maxes and minimums of the process). Furthermore, σ_b is the volatility of b_t parameter.

While short term rate (r_t) might be exposed to high volatility and big shocks, we do not expect such big shocks for b_t. Therefore $dW3_t$ follows a Student-t distribution with 5 degrees of freedom, while $dW4_t$ follows a normal distribution. Note that dt parameter is one hour rate normalized per yearly time, that is $dt = 1/(365 * 24)$.

3.4.3 Default probability

We also model the defualt probability. Because we do assume that investors percieve staking as (somewhat) risky and they demand a certain attribution for the risk that they are taking. We assume that the market estimates that probability and that the staking return is likely to be higher than the risk they are taking (risk of default plus riskless rate in the market, often chose as a return of market treasury). We assume that investors are rational and will not invest in something they deem risky if the return is smaller or equal than a return of the riskless asset.

It is modeled by the following equations:

$$m = (def - ltrdef)^{-1/2}$$

$$Pdefault_t = -2 * (t + m)^{-3} dt + default_t * defvol * dW5_t$$

Here def is the default probability now and $ltrdef$ is the long term default probability. Furthermore, $defvol$ is the volatility of default. $dW5_t$ is again using Student-t distribution (2 degrees of freedom) due to the fact that any bigger shock is likely to influence the default probability in the short term. This could be a new found vulnerability or a new method of making everything more secure. There can also be a change in regulations, or some sudden economical event. We estimate that such vulnerabilities can have quite a big effect on overall probability. If we solve the equation, we find that our expected probability of default is going to be declining roughly x^2 per year, where x is the starting probability of default. This means that if current probability of default is 0.01, then in two years time it will be 1/144.

In order to estimate the long term probabilities of default for a specific platform, we decided to look at the default rates per year. The S&P Global Ratings prepares an annual report on default rates [SP 21], where they also show statistics of default rates over the history. According to a16z crypto 2022 report about the state of crypto [Dar22], the crypto right now is at the same state as internet in 1995. So, we took the starting numbers of default the same as the S&P Global Ratings report in 1995. We assumed that our low risk investments have a similar rating as BBB rated investments in 1995. Medium risk probability of default is the same as BB rated companies and high risk the same as B rated. This nets us with a probability of 0.17%, 0.99% and 4.59% respectively. For the long term rates, we chose the same type of assets, but we looked at the average of the years between 1999 and 2021. Those timelines were chosen because it had two periods of severe downturns (dot com bust and 2008 crisis). Internet companies were therefore already quite mature by then, so we believe that those estimates are relatively realistic. They do not necessarily predict hacking defaults, but in many cases operational and economic ones. However, due to hacks and unstable economics, starting defaults are a bit higher, so it makes sense that our starting defaults are a bit higher too and only gradually decline to their long term values. Furthermore, due to our assumed diversification in each risk pool, we invest in at least 3 different protocols in each pool. This means that our maximum loss is 40%, but on the other hand the probability also increases in such a way that now any one of those protocols can default. This gives us short term probabilities of default for low risk, medium risk and high risk investments at 0.00449325, 0.018188597, 0.0985713 per year respectively. By the same calculation, we have long term probabilities of default at 0.0050913349, 0.02940694, 0.13147627 per year. Note that, while one can say that hacks today are more common, we only inspect the hacks where the money of their clients was lost; as we can see at table 1, those hacks do happen, but they rarely result in the loss of funds for big platforms. Another way of failing is due to users suddenly demanding their funds back. This could be due to the fact that users lost confidence in the protocol or just a very volatile market. Either way, this could result in temporary or long term loss. Temporary loss would be an example when a stablecoin temporarily loses its peg. We will not inspect those cases.

3.4.4 Sum of overall return per period

When calculating the overall return per period, we should first get the probability of default in each period. We do this every time step with the following equation:

$$P_t = (Pdefault_t + ltrdef) * dt$$

where P_t is the probability of default. We add long term default probability in the equation in order to make sure there is always some probability of default. Furthermore, dt is the normalization of probability per hourly level. So, the default probability that we have per year and then multiplied in such a way that we normalize it per hourly basis.

Then we take the uniformly randomly distributed number (between 0 and 1) v_t and transform it in the following manner: $v_t^* = maxinv * (1 - v_t^2)$ Here $maxinv$ is the maximum amount that we can invest in one pool. We then make the returns function in the following manner:

$$dR_t = r_t * R_{t-1} * dt - P_t^* * v_t^* * R_{t-1}$$

By doing so, we ensure annual return and make sure to take into account the probability of default. That is then multiplied with the share of our assets that we lose. Note, P_t^* here is the probability of default (and is generally very low every hour of our simulation). It has a value of 1 if true and 0 if false. This also indicates that when such a shock happens, it is very sudden!

With all of this we therefore have a whole financial model for price simulation. We can make multiple simulations at once since they all depend on random.

3.5 Choice of parameters

3.5.1 Safe portion of staking

We choose several different parameters for our model. Firstly, we have a starting b_0. This is the starting value of long term trend for staking return. Currently we have been seeing a declining staking rates. We assume that we do not know in which market sentiment we will be, so we set b_0 to be a random value between lower and upper bound of b_t. We set the lower bound for b_t in the long term at 0.015 and upper bound to 0.03. By doing so, we assume that long term return on staking will be roughly between 1.5% and 3%. Note, that we are considering the platforms which are well backed, have a good track record and seem to have sustainable returns. We also assume volatility of the long term staking rate. We tried to compare this with the data we have, but the data had infrequent updates and all of the updates were rounded estimations at best. So, we were unable to find a reliable volatility of the staking rate. While not perfect, we decided to therefore estimate $\sigma_b = 2$. We compared it with the data that is available and it did not show big deviations. We tried different volatilities, but they have not changed our results in a major way.

Note that in this paper, we differentiate between staking and deposit pool. When users deposit their coins with us to generate yield, we consider this to be a yield generated by our deposit pool. When they stake their foundation tokens to gain the rewards, that is the staking of foundation token (we do not discuss that in this paper). Furthermore, when we put our treasury reserve in other stablecoin platforms, we call that staking. This is part of our investment strategy.

Based on the data available, we set the starting staking rate, r_0 to be at random between 0.015 and 0.03, so it is the same as current long term rate. This is because we are trying to match a current return. We have the same problem as before with the assignment of volatility. We simply do not have enough data and we only compared it with the data that is available. Therefore we decided to set a volatility (σ_r) of 8. With those settings, we compared the volatility to the short term volatility of staked DAI on AAVE protocol (1 month data [AAV22]) and we found that we do not deviate too much from that volatility.

Furthermore, while the way the investors perceive the market is somewhat set, we allow for very high volatility there with possible big jumps. So, the volatility of their perception (*sigmamkttime*) is set to 2. Lastly, we assume that in case of a safe asset allocation we will allocate at most 40% of our assets to a single platform. We also set the default probabilities in the same way as described in the previous subsection for safe investments.

3.5.2 Moderately safe portion of staking

This version of the future price modeling is dedicated to the part of the assets that we consider more risky. We will diversify more and we will demand higher returns for investing on less reliable staking platforms. Those platforms will not be new, but tested and somewhat trusted by the community. We still completely believe in their economic model, but they do have higher risk or different issues such as hacks, regulatory troubles or similar. We choose several different parameters for our model. Firstly, we have a starting b_0. We assume that we do not know in which market sentiment we will be, so we set b_0 to be a random value between lower and upper bound of b_t. We set the lower bound for b_t in the long term at 0.03 and upper bound to 0.05. This is considered slightly riskier than for the safer approach described above, but still relatively safe. Some newer platforms currently offer returns much higher than that - some more established ones still offer returns in that range. So, we can choose staking providers with relatively high trust rate. We also assume volatility of $\sigma_b = 2$ (which is similar as other portions of staking). Current and long term probability of default are set in the same way as described in the section about the probabilities of default.

Starting staking rate r_0 is set to the same value as a starting long term rate. We also set the volatility of the current staking rate to $\sigma_r = 10$. Note, we will already have some volatility with the long term rate b_t. Based on the limited data we had, we found that number plausible. We use the same volatility for the investor's perception of the market. Also, we assume that in case of a safe asset allocation we will allocate at most 40% of our assets to a single platform. Due to their riskier nature, we decide not to invest more into one platform.

3.5.3 Risky portion of staking

This version of the future price modeling is dedicated to the part of the assets that we consider the riskiest. We will diversify more and we will demand higher returns for investing on less reliable staking platforms. Those platforms will go through our manual checks to ensure that they are stable enough. While we believe that their economic model is stable, we are concerned with their long term viability. So, we only invest a small portion of our investments in those platforms. We choose several different parameters for our model. Firstly, we have a starting b_0. We assume that we do not know in which market sentiment we will be, so we set b_0 to be a random value between lower and upper bound of b_t. We set the lower bound for b_t in the long term at 0.07 and upper bound to 0.1. This is considered quite risky, but there are some platforms that now offer such and even higher returns. We also assume volatility of $\sigma_b = 2$. Current and long term probability of default are set in the same way as described in the section about the probabilities of default.

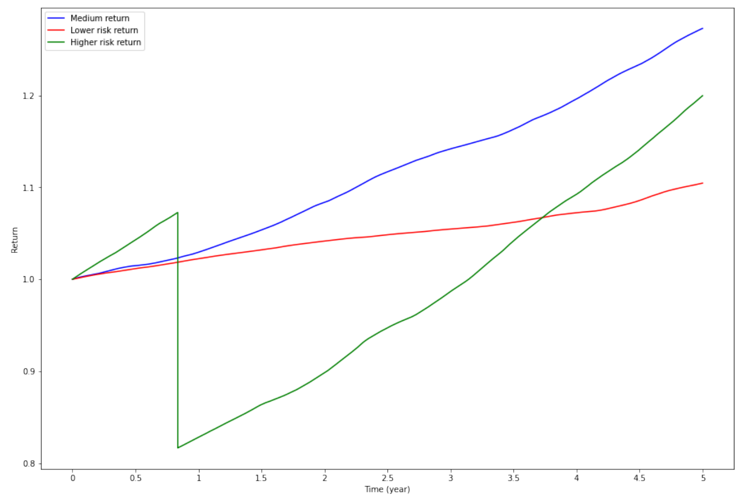

Figure 4: Staking returns over time (sample path)

Starting staking rate r_0 is set to the same value as a starting long term rate. We also set the volatility of the current staking rate to $\sigma_r = 12$, which is slightly higher than moderate and safe portion of staking - higher risk investments have a higher volatility. We use the same volatility for the investor's perception of the market. Also, we assume that in case of a safe asset allocation we will allocate at most 40% of our assets to a single platform. Due to their riskier nature, we decide not to invest more into one platform.

3.6 Simulation results

3.6.1 One path of the return

Here we will explore a sample path and what returns we get with it.

Figure 4 shows a sample return that we can expect in a sample path for 3 different risk assets; low risk, medium risk and high risk. We can see that there was a sharp drop of value for our risky asset around 0.8 years into our simulation. This happened because one of the risky investments defaulted or got hacked. When we invest in risky pool, we diversify the investments into at least three different platforms and maximum loss is therefore decreased - the loss from one platform defaulting is therefore limited. So here one of the platforms we invested in defaulted and we lost some or all of our assets in it. In this specific case, we lost 23.88% of the assets in high risk pool. Otherwise we can see that the returns are relatively stable, though they do vary over time and market conditions. This is in line with low risk asset investment; we expect relatively low volatility. Figure 5 shows how the rate of return for staked assets changes over time and market conditions. We expect change of value for the most time, depending on what kind of market situation we are in. We can see

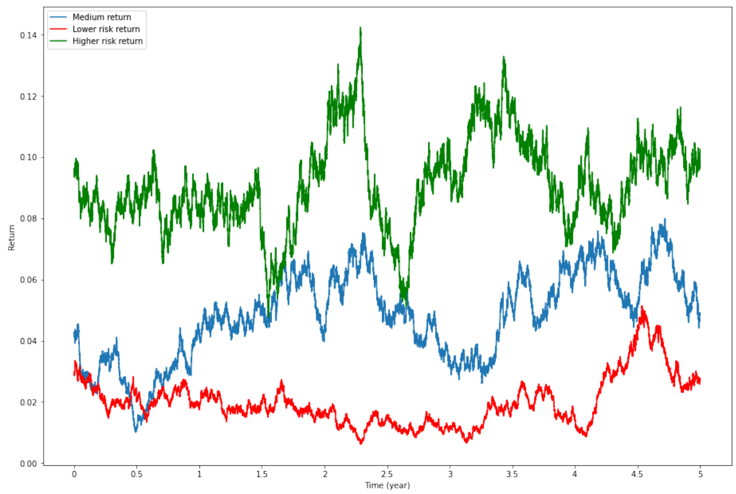

Figure 5: Current staking returns over time (sample path)

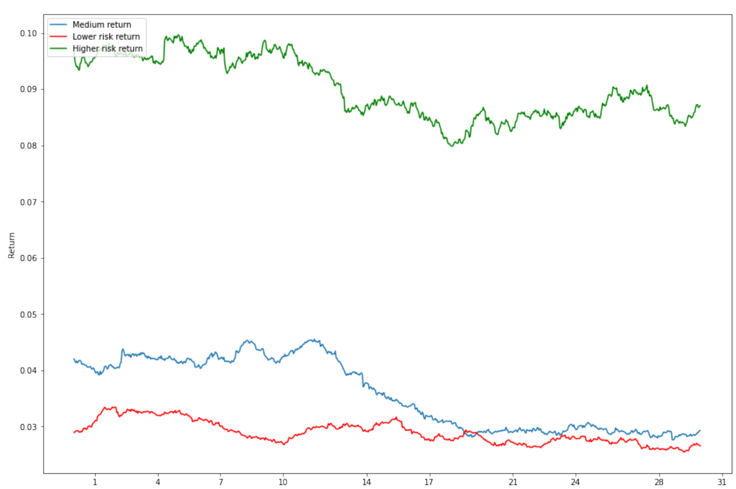

Figure 6: Current staking returns over a month time (sample path)

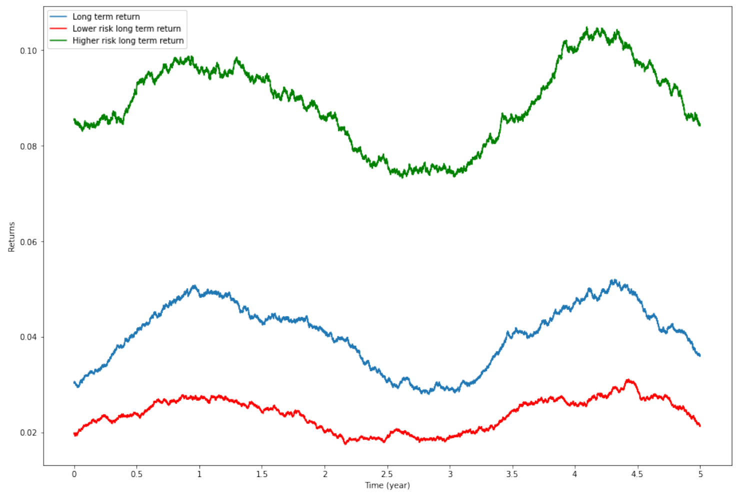

Figure 7: Long term staking returns over time (sample path)

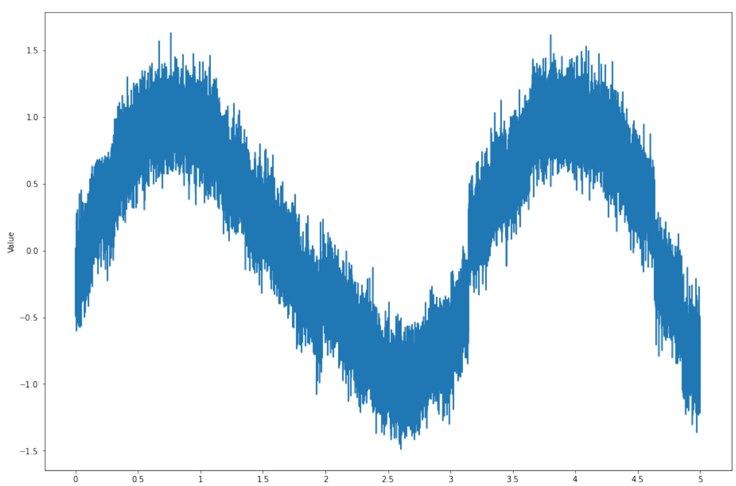

Figure 8: Capturing the market sentiment, which has a numerical value (sample path)

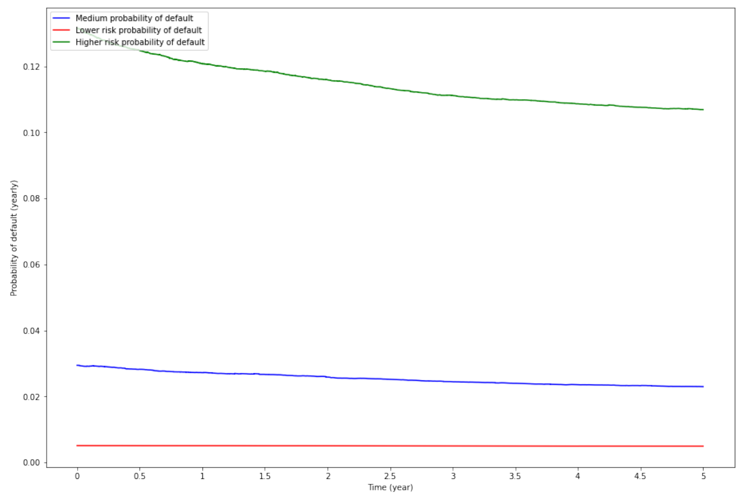

Figure 9: Probability of default for different risk assets (sample path)

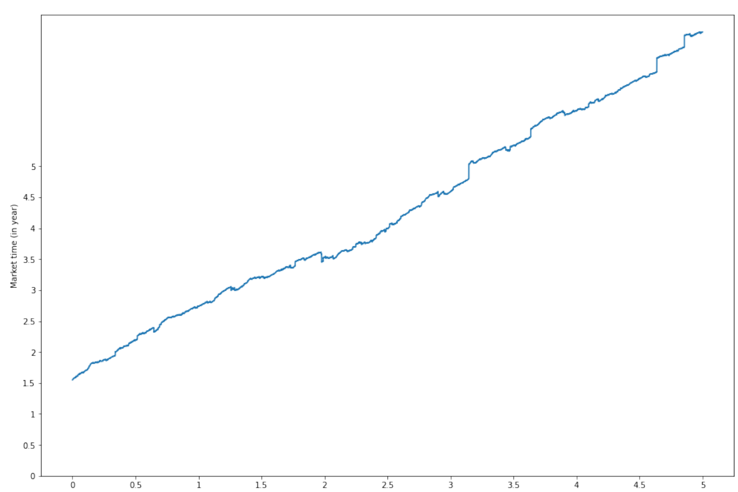

Figure 10: Market time development over time (sample path)

that this is a quite volatile figure. This is because it depends supply and demand for staking, which is (at least for now) not completely stable. We can see what kind of volatility we have in the first month in figure 6. It is slightly lower than current volatility on AAVE [AAV22]. But we do think the AAVE's volatility will improve as the market matures more. Note that it can happen that higher risk assets can temporarily have lower return than low risk; however in the long term this should not happen. This is a market mispricing which can happen quite often in the shorter time frames. Figure 7 shows the long term staking return, which is somewhat related to short term one. It is still somewhat volatile and it depends on market conditions. However, we can see that in the long run it rarely if ever happens that a higher risk return would have lower return than the lower risk return. In the long run we assume our market participants are rational, so they will not invest in riskier asset if it offers them a lower return than the other asset with lower risk. This is unsurprisingly also the case in our sample simulated path.

All of the returns (low, medium and high risk) have been done in the same market sentiment, which is plotted at figure 8. There we have quite predictable path, reaching two positive sentiments (after around 0.7 and 4 years) in our simulation and two negative (after around 2.5 and 5 years). They come from corresponding figure 10, which in our case is also moving quite predictably. Note that it is modeled with Student-t distribution and it could have huge jumps, but that did not happen in our sample path. Last but not least are the probabilities of default and how they change with time. They are plotted at fiugre 9. We can see that they decrease relatively steadily over time as the market becomes more mature and prepared for different events that might cause us to lose funds.

3.6.2 Monte Carlo simulated returns

In simulated returns, we took 10,000 different randomly generated paths and analyzed some statisitcs out of it. This helps us declare how our return is going to behave in normal and extreme conditions when less common events happen. The latter helps us with our risk management and preparation for extreme events. In figure 11, one can see the average returns that we can expect, together with upper and lower bound for our low risk investments. Averages are reduced a lot by extreme events (bankruptcities, defaults, hacks) that happen in rare cases. This is why average is very close to lower bound at the beginning. Later on, there are more shocks and eventually lower bound of the returns deviates slightly from the average. Shocks happen and have a significant effect on the returns. In order to better understand the frequency and the consequences of those bankrupticities and rare events, we also plot 1st, 5th and 10th percentile of the returns in figure 12. Given the fact that we assumed that the probability of default of low risk assets is quite low (and hence the name low risk assets), we can see that those defaults only start to hurt us in the lowest percentile of the cases and even there the defaults hit that percentile around 1.5-2 years in the simulation. While we can definitely lose money there, this happens very rarely, so this seems to be a safe investment compared to other investments that we make. In figure 13, one can see that the average rate of return is quite stable at around 2.25%, but can vary between a bit over 1.5% to as high as 3%, which is in line with our assumptions. It is related to expected market sentiment. We can see a similar story for b_t value in figure 14. In figure 15 we can also see how the market sentiment is changing over the time. We do expect to have some periods of better and worse market sentiment, but due to the randomized start of our simulation (where we take the randomized assumption on which time period we are in in terms of market sentiment) and the fact that we allow for big jumps of sentiment due to Student-t distribution, we have quite wide bounds on what is the expected average sentiment. Some minor bumps are the consequence of sinusoidal function, which is keeping the sentiment within the bounds. Figure 16 shows the average probability of default and how it differs over time for all assets. We can see that it is quite a predictable path, since we assume that it follows a predictable pattern in the long run. Since currently the lowest risk platforms are owned by some relatively big and established companies, we believe that their probabilities of default will not reduce much more (since they are already low). But they will still decrease and in order to have the ability to analyze them better, we also plotted them in figure 17. We can see that there is still some decrease, albeit less pronounced.

Similarly, as lower risk assets, we analyzed medium risk assets. The returns are plotted in figure 18. While on average, medium and upper bound we can see a similar story as for lower risk returns (except the fact that returns are a bit higher and that average has decreased a bit compared to median due to a high number of defaults), we can see that in lower bound it is significantly riskier. This is because many of the investments have defaulted. In order to better inspect this phenomena, we also looked at the lowest percentiles in the figure 19. There we can see that in the lowest percentile is largely hit by the defaults, however it does not seem to happen that in 99% of the cases we would have 2 or more defaults. So, we drop for around 32% and then grow in this lowest percentile. It is a bit better for 5th percentile, where we start being affected only after roughly 2 years. Lastly, in the 10th percentile of the cases we still expect some defaults to lower our returns. This means that the risk in medium risk assets is relatively high. We plotted the returns at figure 20. The average is around 4% and it is most of the time between 2% and 6.5%. While we expect long term returns to be within much smaller range, the actual returns might not have such a small range since they are very volatile. However, we can see in figure 21 that long term return is still between 3 and 5%. Even here we somehow follow sentiment which does have ups and downs in our simulation.

Finally, we made the same analysis for high risk investments. The returns on our assets are plotted in figure 22. There the difference between average and median is even bigger due to a large number of defaults that happened. Lower bound is therefore very negative - but the upside is that the returns in upper bound are much higher, which is an expected feature. We can get an interesting overview on the risks in figure 23. There we can see that according to the lowest percentiles we are very often experiencing one or more defaults and if we only invested in high risk assets, we can easily lose over 50% of our assets in 1% of the

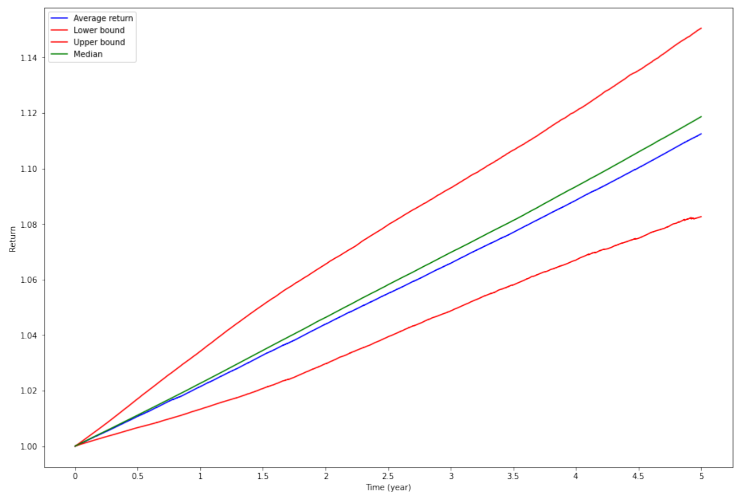

Figure 11: Staking returns for low risk investments (averages and upper/lower bounds)

most negative outcomes. This is what makes them risky. So, we always have to invest in those assets with caution since they can infer a lot of damage on our network and our returns. It is not surprising that the volatility of the returns is the highest there and we can see that plotted in figure 24. The returns can go all the way between 5 and 13% in the long run. However, the long term returns have a smaller volatility and we can see them plotted in figure 25. They follow similar patterns as for low and medium risk investments there.

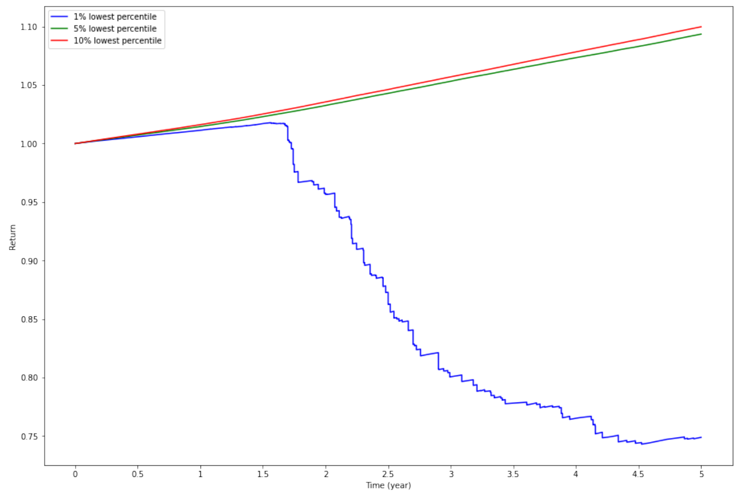

Figure 12: Staking returns for low risk investments (lowest 1st, 5th and 10th percentiles of simulation)

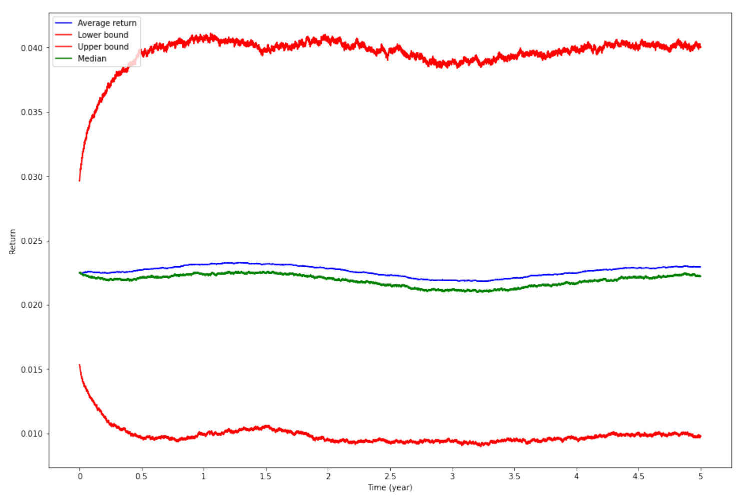

Figure 13: Current staking returns for low risk investments (averages and upper/lower bounds)

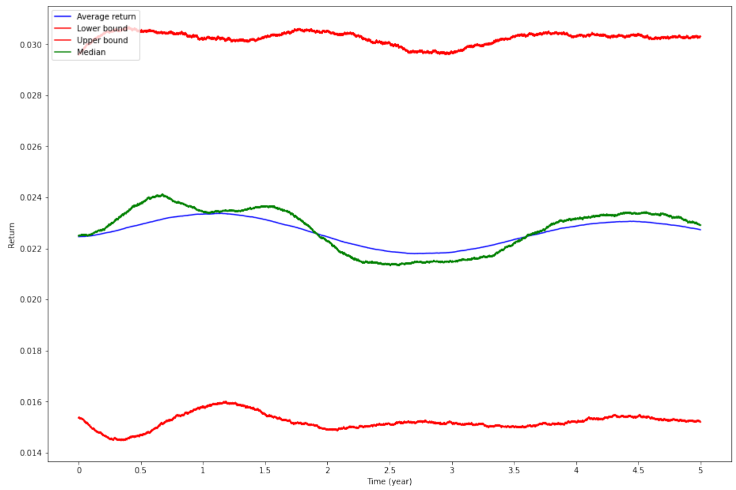

Figure 14: Long term staking return for low risk investments (averages and upper/lower bounds)

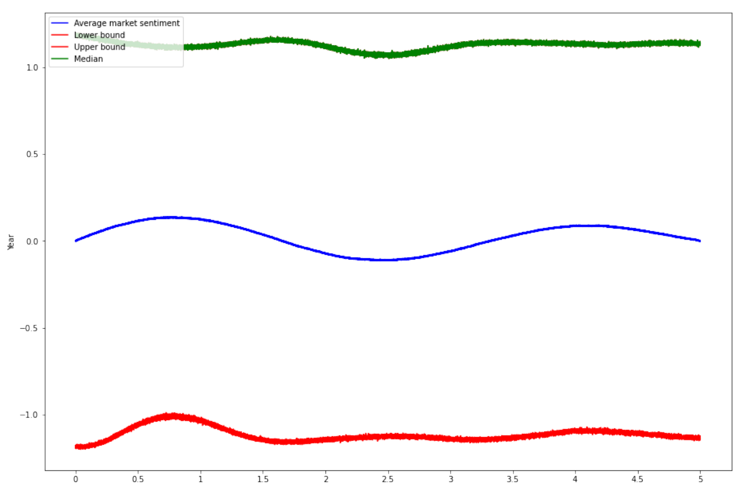

Figure 15: Capturing the market sentiment, which has a numerical value (averages and upper/lower bounds)

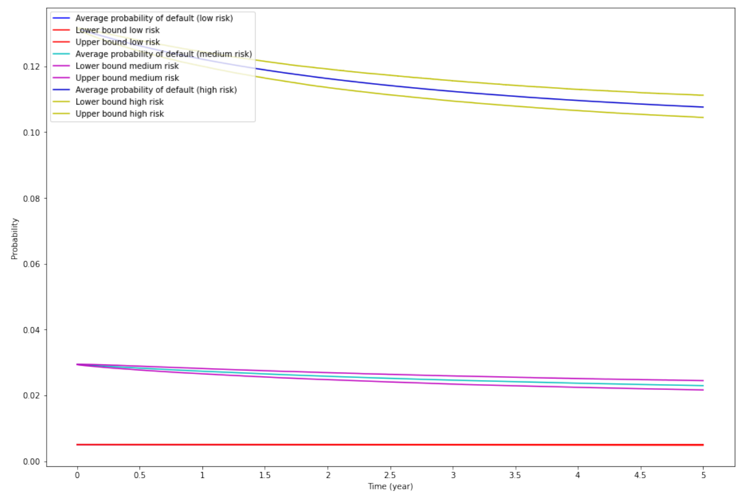

Figure 16: Capturing the probability of default for different risk strategies (averages and upper/lower bounds)

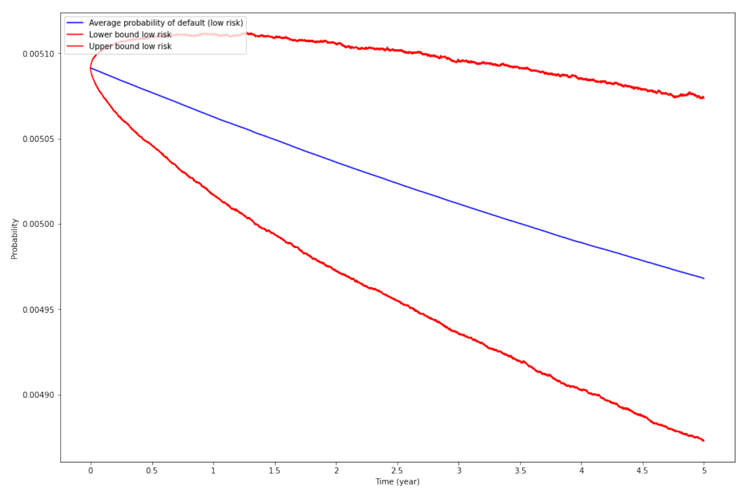

Figure 17: Capturing the probability of default for low risk strategies (averages and upper/lower bounds)

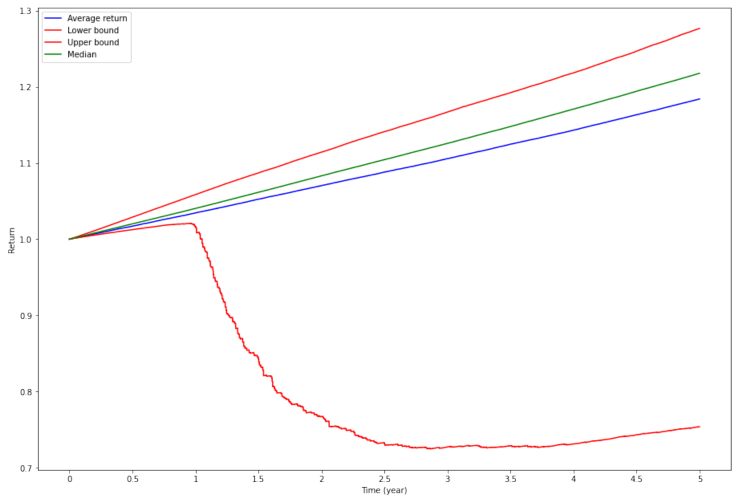

Figure 18: Staking returns for medium risk investments (averages and upper/lower bounds)

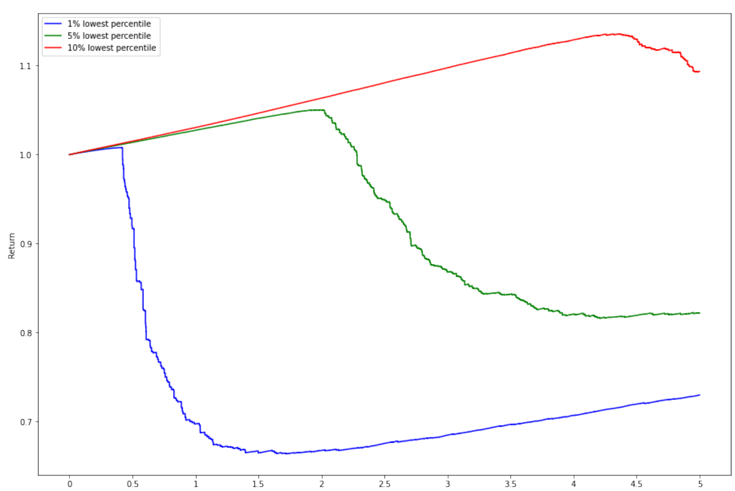

Figure 19: Staking returns for medium risk investments (lowest 1st, 5th and 10th percentiles of simulation)

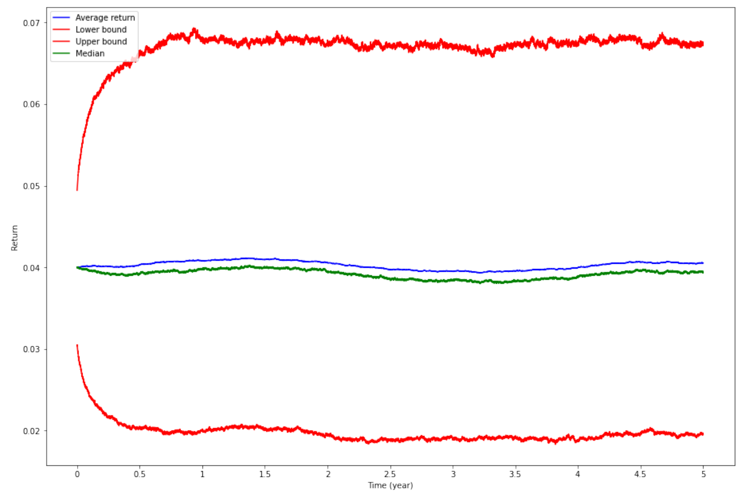

Figure 20: Current staking returns for medium risk investments (averages and upper/lower bounds)

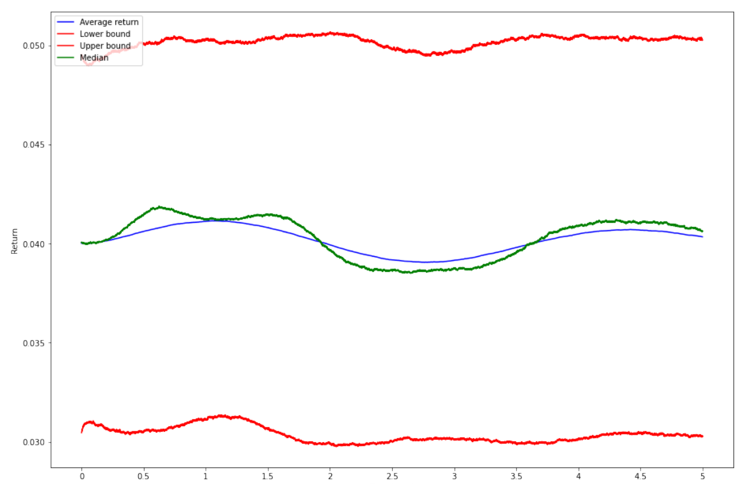

Figure 21: Long term staking return for medium risk investments (averages and upper/lower bounds)

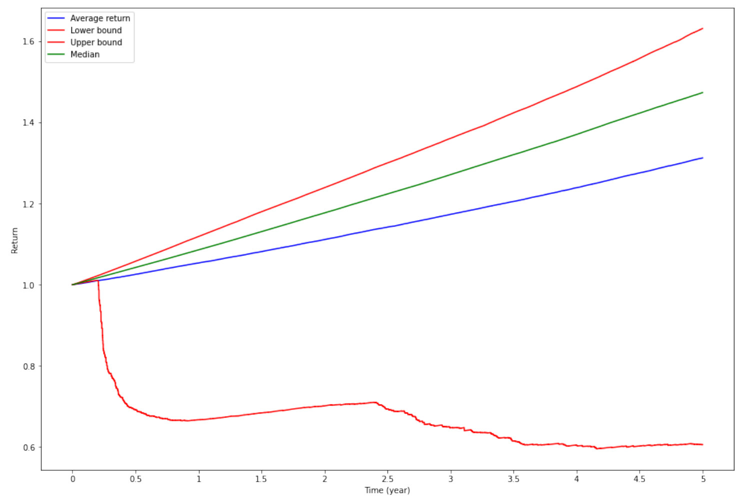

Figure 22: Staking returns for high risk investments (averages and upper/lower bounds)

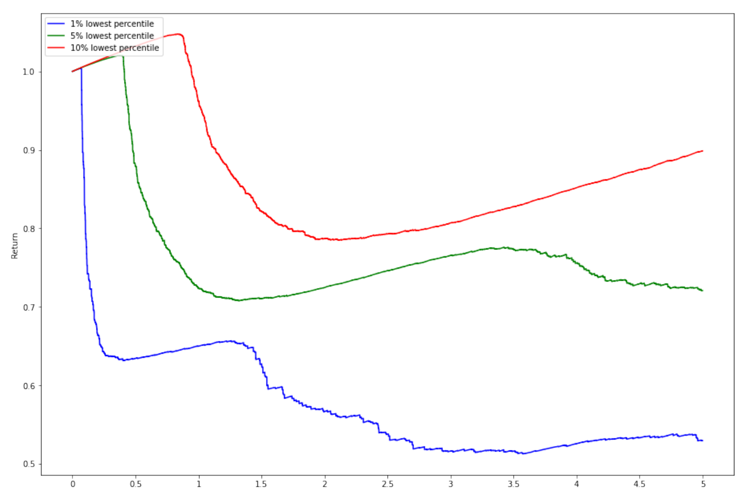

Figure 23: Staking returns for high risk investments (lowest 1st, 5th and 10th percentiles of simulation)

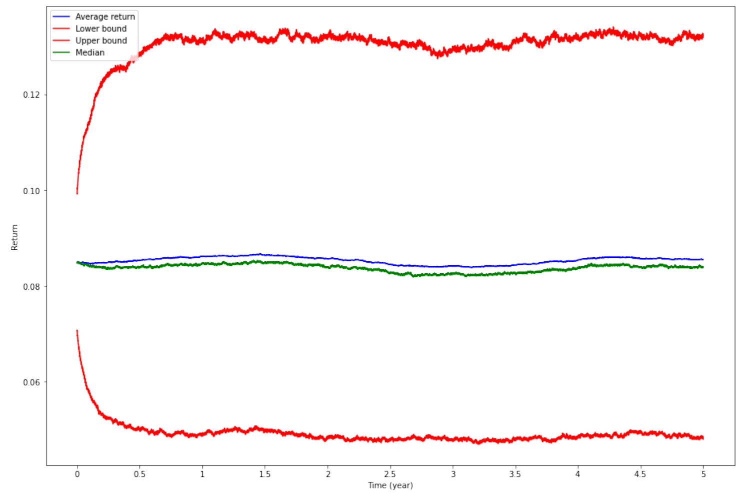

Figure 24: Current staking returns for high risk investments (averages and upper/lower bounds)

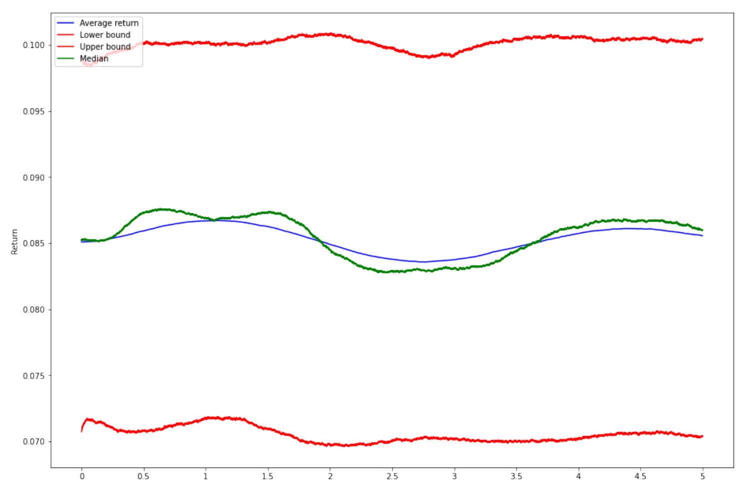

Figure 25: Long term staking return for high risk investments (averages and upper/lower bounds)

4 Modeling the growth of the network

In the following section we estimate the growth of the usage of the platform. This is the influx or outflux of the money to and from our coin. We have investigated several different coins (mostly stablecoins) for their growth and development over time. We tried to model our growth as realistically as possible by modeling different market conditions and different events that can trigger either a run on our coin, a big change of the ownership, and other events. This is useful as an estimation of how our economy will look like as well as for the possible stress tests that we can perform.

4.1 Research on other stablecoins

We have decided to mainly research other stablecoins. This is because they also have a backing behind them and a degree of market confidence. Degree of market confidence in a big way determines their success and we believe it will be an important factor for us as well. We have the data for the market caps and the amount of tokens in circulation as well as the number of holders for many coins, but many of them pose a problem for our research. The older stablecoins are very centralized and can, if they want (and they probably do) have some of their coins in their own wallets while they could have been burned (or bought back). That gives them the market cap and promotion, so more people use them. The stablecoins with bigger transparency only appeared in recent years, mostly with the emergence of DeFi. Their data is much more transparent and we can see the growth more clearly there. This also helps us with determining the actual demand for our prospective coins. Furthermore, we also tried to check the amount of users, although this only inspects the number of active addresses and this number can be manipulated again. The more important number is the number of coins in circulation. We gathered data for the latter (historical data that is) for DAI, RAI Reflex, FRAX, USDP and TUSD. The reason for this coins is that some of them are in DeFi (DAI, RAI, FRAX), have relatively similar tokenomics as we plan to have (at DeFi coins, even though this is only true to a certain extent) and have quite reliable data. Furthermore, we have studied their business success, which helped us build a model for stablecoin growth that we can implement for ourselves as well.

DAI is the biggest DeFi stablecoin and offers a lot of usable data that we can inspect. RAI Reflex is a coin that implemented several innovative solutions that have not completely caught up yet, such as automatic portfolio management, redemption fee and others. We do plan to take some of their innovations and adjust them for our purposes. FRAX is another DeFi coin that has gained a significant traction despite having only partial collateral. USDP is another popular coin, which has lost a bit of popularity and traction due to other coins being more popular. But it still achieved growth and enjoys respectable stability. Similar can be told for TUSD, which also has stable reserves and quite a bit of usage. They all have the data that we need to analyze them.

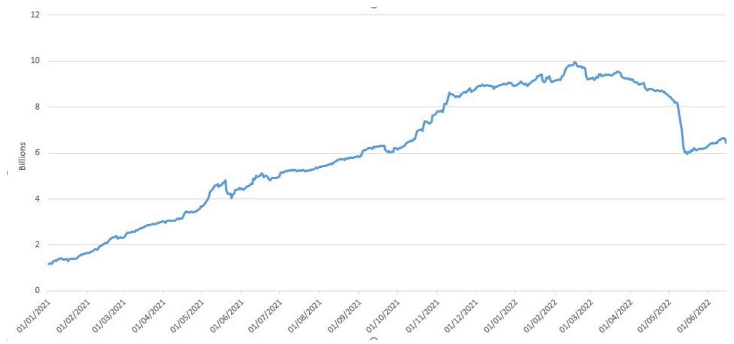

Figure 26: The growth of the number of DAI in circulation from January 1st 2021 to June 14th 2022

4.1.1 User growth

While we did not model user growth (although we might do that in the future versions of financial modeling), we were still interested to see how it grew for several different coins in order to understand their marketing and popularity. Especially for those that are on DeFi, it is common that the coins are widely kept in private wallets (because they are then often traded directly through decentralized exchanges and not kept on a centralized exchange for trading). This gives us a better overview on the amount of users and their growth. We found that DAI had a long and steady growth, while FRAX had a very fast growth between July and January, which has then gradually slowed down. This indicates that it was getting an increased hype in that time, which has then slowly died out. Finally, RAI Reflex got a lot of users at the beginning of their launch, but has since kept them steadily or they were even declining. We got the data from Dune.com. One can find our research here: [nej22b], [nej22a], [nej22c]

4.1.2 Growth of the market cap

The five coins that we have described in the beginning have then been studied regarding the growth of the network. They were created in different times and developed in different ways. While we did study their whole timeline in order to be able to analyze their growth and develop a model that would follow it relatively closely, we will show the results of their growth from January 1st 2021 until June 14th 2022. Note, we got the data from coingecko.com (accessed on June 15th 2022). We will briefly present each one of those five networks and their growth in that time frame.

4.1.2.1 DAI growth

DAI (as seen in figure 26) grew relatively steadily until around February 2022. There were different reasons for the fast growth, such as an increased popularity

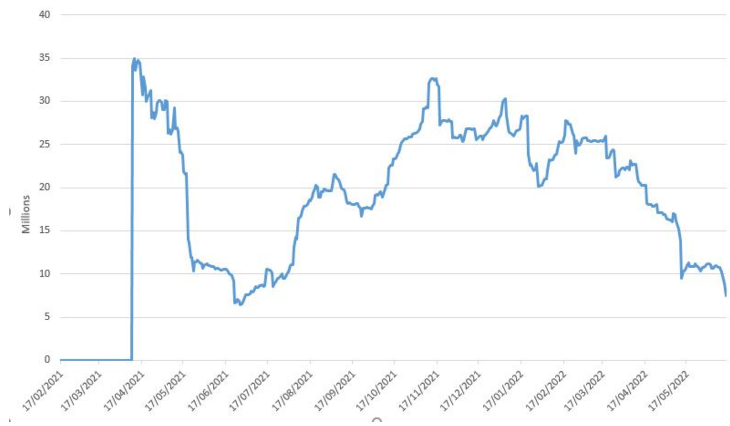

Figure 27: The growth of the number of RAI in circulation from January 1st 2021 to June 14th 2022

of DeFi, quick adoption, momentum and also possible staking returns, which were still a relative novelty in 2021. We explore a gradual decline in DAI after March 2022 and a sharp drop in May - which was an external shock. It was around the time that LUNA capitulated, having lost its peg and causing a mass run out of assets in almost all cryptocurrencies [hea22]. It has since then stayed volatile, despite recovering ever so slightly.

4.1.2.2 RAI Reflex growth

RAI (as seen in figure 27) did not have the data for the whole time period observed. It had the data from roughly mid April 2021 and onwards. So, we look at the shortened time frame. Besides that it had some small issues at the beginning with the peg. Anyhow, it then fell and grew again. It is hard to replicate this due to volatility and a lot of random events that happened. It had a a redemption fee and an automatic collateral control. It's price is around 3.14 (π price), however it did not have a massive success to catch on. It is also quite hard to get a good staking return on those coins. It's popularity was slowly fading in 2022 and RAI too got hit by the UST crash [hea22].

4.1.2.3 FRAX growth

FRAX (as seen in figure 28) has started existing just a little before January 1st (Coingecko has a history since December 21st 2021). It has initially grown very slowly, but it got very popular in second half of 2021 and at the beginning of 2022. After that it was roughly maintaining the amount of money in it until the UST collapse happened. At that time it lost almost 40% of its market cap and then stayed roughly the same. It was not fully collateralized, got a lot of hype from the cryptocurrency community and had staking options available (so one could earn money by staking it).

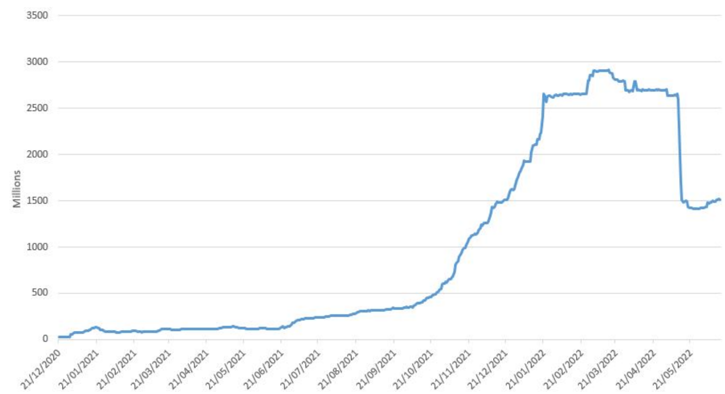

Figure 28: The growth of the number of FRAX in circulation from December 21st 2020 to June 14th 2022

4.1.2.4 USDP growth

USDP or PAX (as seen in figure 29) has been around for a while. It might have lost a bit of a hype it once had, but at least in the beginning of the 2021 it was still quite popular among the investors. Around May in the same year it lost some of the popularity, but maintained roughly the same amount of tokens. While the graph does not show that it was hurt by UST crash, it is still possible that it had to buy a lot of its own tokens in order to maintain the peg, but it might not throw them away (burn them) like some algorithmic projects. Still, it has relatively low amount of hype, solid collateral and average staking returns.

4.1.2.5 TUSD growth

TUSD (as seen in figure 29) is also a bit older coin. It is also backed by assets such as bonds and treasuries. It is not algorithmic and has as such not enjoyed the hype that some other coins did. But it still offers good staking returns on some platforms and had some momentum in the first half of 2021. Since then it has lost a lot of momentum, but somehow maintained the amount of tokens. It was hurt by UST crash, though we might not have seen the true extent of it on blockchain.

4.2 The growth model

In our model, we tried to take into account several things that we will describe here.

Collateral: We model both collateral and CAR in our model. The latter is better explained in our whitepaper [Pus22], but it discounts the assets based on how risky they are, similar as it is done in Basel III rules [Tea22]. Ideally we want to hold our collateral ratio above 1. We are fine with having the ratio below one, so long as it remains healthy enough to keep the project solvent. If our collateral ratio is low, then the market might get cautious and decide to not

Figure 29: The growth of the number of USDP in circulation from January 1st 2021 to June 14th 2022

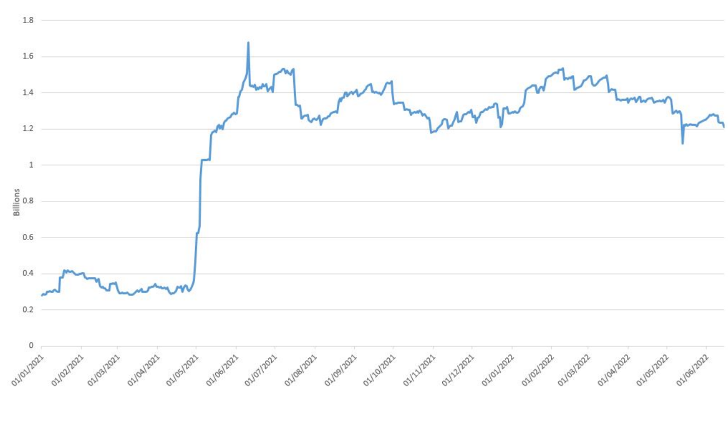

Figure 30: The growth of the number of TUSD in circulation from January 1st 2021 to June 14th 2022

invest in our coins. Furthermore, if the ratio is very low, the investors might worry that their assets are not fully backed and that not everyone will be paid - causing a massive run on our coin and possibly selling it off (such an event will be referred to as a coin run). LUNA (UST) situation might happen in this case. This means that users make a run on our coin and we are not able to back it up. Furthermore, if we keep such a ratio and users start redeeming at a higher level than we can guarantee, that causes us to deplete our reserves even more, pushing collateral ratio down even more and increasing a likelihood of a collapse. It is a negative self fullfilling prophecy, which we are trying to avoid. This is the same for stablecoins. Some of them failed because of that and we want to model it in such a way that a low collateral can be very detrimental to growth and can even cause the collapse of the system.

Hype: Hype is hard to model, but it is apparent that DeFi projects had higher adoption than others. It was a time of a boom in that industry, which relies heavily on decentralization. Investors also like the idea of decentralization in cryptocurrency, so such projects are likely to get a lot of hype. While we do not rely on a hype ourselves in this model, it helped us to model the success of some other coins. With other words, it helped us explain their success.

Staking returns: While stablecoins usually do not offer staking, some platforms offer different rewards for staking the tokens there. With this one can earn a return with a stablecoin. This is very tempting for stablecoin users, since it is (relatively) low risk return. The return is not high and it can happen that protocols can be hacked or fail, but this does attract new users. If there is a possibility for a stablecoin to get higher returns than one can get in other stablecoins, this is a competetive advantage and one can expect slightly better performance of such a stablecoin if all other things are the same.

Market sentiment: We have modeled market sentiment as a major factor when it comes to staking returns. We believe it has a huge effect also on the growth of the stablecoins. The graphs that we showed before (growth of the selected 5 stablecoins) shows that in the time that market conditions were not the best, most coins either lost invested value or kept it the same. So, this in general plays a major role.

Momentum: If we get a sudden adoption, more people start talking about the coin, driving more adoption. This goes the other way around (sometimes very painfully). If everyone is exiting their positions, this just amplifies the herd behavior.

Index return: This is something that does not exist among the stablecoins. They do not offer higher returns by just holding them (or lower, depending on the index). However, offering returns by just holding does add another stream of income for users. We believe new users might be attracted by positive returns and scared away by the negative ones. So, this will influence the influx of the users. Unfortunately we were unable to observe other projects to determine just how big this influence will be. So we made some assumptions here.

Unexplained volatility: There is a level of volatility that is unexplainable by other parameters. Other parameters should be able to explain the growth quite well (and are volatile themselves), but there is an extra level of volatility, albeit relatively small that is still unexplainable.

Extreme events: Events that happen very rarely, but they happen. We are usually not prepared on them. An example of a recent such event was UST crash. Now that the regulation is coming, such events are less likely, but not impossible. A reminder of such an event (outside of crypto) would be also a global pandemic that happens once in more than 100 years. Usually we do not fully expect it until it happens.

4.2.1 Mathematical specification of the model

Our model is as follows:

$$\begin{split} dG_t = month_t * M * G_t * dt + i_t * G_t * C_i * dt + \frac{col_t - 1}{col_t} * C_{col} * G_t * dt + \\ (dep_t + i_t - stake_t) * C_{dep} * G_t * dt + us_t * G_t * C_{us} * dt + \\ C_{msent} * (msent_t)^{-\frac{sign(msent_t - msent_{t-1}) - 1}{2}}) * abs(msent_t)^{\frac{sign(msent_t - msent_{t-1}) + 1}{2}} * G_t + \\ G_(t-1) * brun_t * P_t^b + \sigma_G * dW_t^5 \end{split} \quad (1)$$

Note, sign is the mathematical expression that checks if the value is positive (returns 1) or negative (returns -1) [Wik22]. The explanation of variables:

G_t: Our network at time t.

$month_t$: the increase of our network between time t and one month ago. If our history is smaller than one month, then its value is 0.

M: momentum constant. It shows the weight we have on momentum.

i_t: index increase (or decrease if negative) that we can expect in the next 3 months. Note, we assume that market participants know the exact increase in index for at least 3 months in the future.

C_i: index constant. It shows the weight we have on index.

col_t: Our collateral ratio at time t.

C_{col}: Collateral constant. It shows the weight we have on collateral.

dep_t: deposit rate at time t.

$stake_t$: The rate of staking that we can get on the market at time t. This is (in our model) the same as the rate at moderately risky scenarios.

C_{dep}: Deposit (plus index) constant. It shows the weight we have on this part of the equation.

us_t: usage (or hype) at time t. This is modeled as a random process in our model.

C_{us}: usage constant. It shows the weight we have on usage.

$msent_t$: sentiment of the market at time t. It is what we defined as a state of the market in time t.

C_{msent}: sentiment of the market constant. It shows the weight we have on sentiment of the market.

σ_G: is the constant that adds to the general volatility of the process.

dW_t^5: is a random process, distributed using Student-t distribution with 5 degrees of freedom (and therefore allowing for fat tails).

Furthermore, we define a process:

$$dus_t = \sigma_{us} * dW_t^6$$

where

dus_t: is the derivative of us_t, the process we have for usage.

σ_{us}: standard deviation of our usage.

dW_t^6: Random proces with Student-t distribtion with 3 degrees of freedom.

$brun_t$: Process, that is equal to 0 at all times except when the bank run happens. Then it has values different than 0 for m hours, where m is constant that is randomly chosen.

P_t^b: Is the process that shows that a bank run happened and lasts at time t. While the bank run happens suddenly, it does last several hours, so P_t is not exactly a probability. Furthermore, it is equal to 0 at all times except when we have a bank run. Such an event, together with the model for process $brun_t$ is described later on.

This means that the growth of the network depends on several different processes. It does depend on momentum (monthly growth). It depends on collateral in such a way that if this ratio is low, its weight increases by a lot due to the fact that we have it in denominator. As it approaches 0, the value converges to infinity, causing a negative influx in the network - a run on assets. We also modeled the difference between deposits and index growth and how much one could get from staking elsewhere. If positive, this coin is most likely a better investment than others, causing a further influx of funds. We also made sure that the usage is taken into account. A big part of the latter is a hype of which many coins have profited lately.

The final non-random variable here has to do with the market. We can see that in the past there was a big increase in stablecoins in circulation when it came to bull markets and only a minor decrease when it came to bear markets. If market confidence is high (above 0 when we have sinusoidal process), then if it is growing, the adoption of those coins grew fast. That meant that the market was increasing and the demand for borrowing and investing could not catch up the demand that users offered. When it was high but decreasing, there was still a positive demand. Perhaps people and institutions didn't borrow and invest more, but there was still a slow growth. Those are the times that one could describe as a crypto autumn. The things are nice and growing, but at a much slower pace and the growth is losing it's momentum. Typically the projects still have good revenue here and manage to attract a lot of new users and money, so in that time we expect to grow. But the growth is slow in such a case. But in case when the market sentiment is negative and decreasing, this is when we can expect fast decreases in new users. Furthermore, the last option when market sentiment is negative but increasing, this is the time of the early adoption, when there are first signs that the demand for coins is about to increase. The demand here is increasing slowly at first. Those periods are not expected to behave in straightforward manner. So, there will be positive and negative jumps at each of those periods. But this part of the equations checks in which part we are and models growth or decrease of value accordingly. It seems that the stablecoins have mainly lost value in crypto winters, while in the other periods they had the influx of funds. A big reason for that is the fact that we have seen a general growth of demand for stablecoins in recent years, so we have mainly seen them growing in value.

In case a bank run happens, we have modeled that it lasts for m days, where m is a randomly generated integer number. It is randomly and uniformly chosen between two bounds, that are better described in a section "Our model". $brun_t$ is then modeled as follows:

$$brun_t = (1-p)^{1/m} + \sigma_{amountlost} * W_t^7 * (1-p)^{1/m} \tag{2}$$

Where:

p is randomly uniformly chosen between 0.2 and 0.4 and represents how many assets we will lose in our time frame.

m is an integer that tells us how long the bank run will last.

$\sigma_{amountlost}$ is a volatility parameter, set to one that adds the volatility to that process.

W_t^7 is a random process, using Student-t distribution with 5 degrees of freedom

t in this case goes from time t_0, when we hit that probability (so, when the external shock happened) to $t_0 + m$. At other times this process is equal to 0.

The last part of the equation is the random variable that adds some randomness to the coin run, making sure that there are some random jumps as well. Those could be considered marketing events or general market behavior that is usually hard (if not impossible) to predict.

Furthemore, as a last addition to the model, we check the change and if it was positive, we do nothing. If it was negative, we check for how much money is staked in long term staking or deposits for each coin and reduce the outflow of money based on that number. The reasoning behind that move is that those people that have staked are unable to switch the money to other coin (because it is locked). In this way we can more accurately model behavior of the markets - some amounts of the coin cannot be redeemed because of that reason. The equation is:

$$G_t = G_{t-1} + dG_t * (1 - \frac{abs(sign(dG_t) - 1)}{2} * d_t)$$

where d_t is the share of depositors in time t.

4.2.2 Fitting the model on real data

We wanted to make sure that our model is robust and can predict the actual events that have happened. We have the data for 5 different coins that we described. Unfortunately we do not know all the parameters and processes, so we made a very rough estimation of them. As such we were bound to fail to predict the actual growth of those stablecoins accurately, but we can still expect to be reasonably close to the real world, if we just round up the rough numbers and set them as constants. If our model can be at least close to forecasting actual gains of real projects, then we believe it is a reasonably good model for forecasting our coin as well.

Before we got to estimating the values for specific stablecoins, let us first discuss roughly how fast DeFi coins were most likely growing compared to other stablecoins. If we look at the growth of DeFi on coinmarketcap [Coi22] for one year, we can see different outcomes. If we take a time period from March 24th 2021 (the first record of this website that we have available on archive.org) until March 18th 2022 (we do not have records available for March 24th 2022 on archive.org), we can find that the growth of DeFi was around 50%, while general cryptocurrency grew 11%. However, if we take timeframes a bit later, we can see that general cryptocurrency growth (which was negative) was higher (or less negative) than DeFi. So looking at purely market cap is not a good idea because DeFi has much more volatile market cap. According to [CL22], cryptoccurency is expected to grow with 12.2% CAGR and according to [Res22], DeFi is expected to grow at 43.8% CAGR, which is way faster than general cryptocurrency. However, it is still likely more prone to the general market volatility. In our time frame (2021-mid 2022), it likely grew much closer to general cryptocurrency (that growth was actually projected for future, not for past), at least in stablecoin markets. Biggest stablecoins remained USDC and USDT. DeFi is more than just stablecoins and other parts of the industry likely grew much faster (NFTs for example), which adds to the total growth. So, we estimated a rough 8% higher growth for some bigger coins and faster for the smaller ones if they caught off to the hype.

Also, in this fitting we excluded all the volatility in order to just get a rough idea of the growth. We will have a much more real and big volatility in our actual simulation. Furthermore, we have set the market sentiment to be gradually falling to our assumed point that we got according to the current staking returns and our opinion of what happened given the understanding of the model. Note that market sentiment in cryptocurrency decreased by a big margin recently and we tried to model that. We can see our assumed market sentiment in figure 31.

4.2.2.1 DAI model

As described, DAI is an algorithmic stablecoin. Its growth came from a positive sentiment in the market, relatively good staking returns and good collateral ratio. Those were all changing during the period of 1.5 years that we have observed the data (see figure 26). However, to make a quick assessment of the validity of our model we chose to set them as constant. So, we have set up the hype parameter us_t to 0.08 over the whole timeframe. This parameter rarely stays fixed on a specific number, but here we are taking some assumptions. This represents DeFi and to a smaller extent DAI hype that happened mainly in 2021 and early 2022. We set deposit rate to be 1% higher than the market

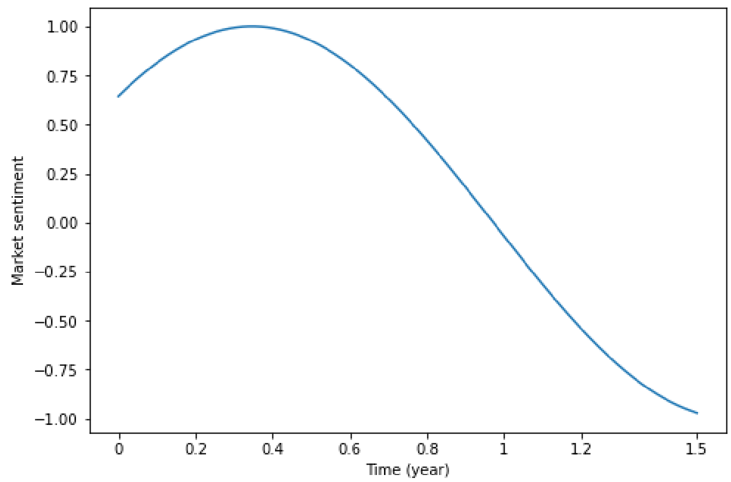

Figure 31: Our assumed market sentimet

deposit rate (meaning that returns that one got by staking DAI were slightly higher than average of other coins) - it is something we have observed in shorter term (however, we do not have longer term data to check the validity of that). We assumed constant collateral ratio of 1.3, which is in line with the current collateral ratio. We assume 5% of the people have staked DAI for longer term (so they cannot redeem it in the event of an asset run to that coin). For none of those coins we assume index growth (because they don't have one in their design). We start with the same amount of tokens as DAI did have in January 1st 2021. As can be seen in figure 32, our simulated growth, while not the same as the actual growth displayed in figure 26, is not too far away. Given that our parameters were superficially chosen, this is a relatively good approximation. Note that we have started with 1.1 billion tokens and moved on up to almost 16 billion in our simulation versus the reality when it only hit around 10 billion. It is still very close, since we have captured most of the growth. We also did not include volatility.

4.2.2.2 RAI Reflex model

RAI Reflex is an algorithmic stablecoin. It did not catch up too well and had some troubles with pricing at the beginning. This made our estimation harder, since there were a lot of outside factors affecting their growth. It is not necessarily simple to get staking rate for RAI, so returns are assumed to be 1% smaller than the market rates. They are automatically collateralized, so we assume collateral ratio of 1. RAI was expected to have a quite big hype (because it was a very innovative DeFi project), but it did not live up to the expectations. We still assume 2% hype and 1% of the asset deposited in longer term staking pools. We start with the same amount of tokens as there were at the beginning

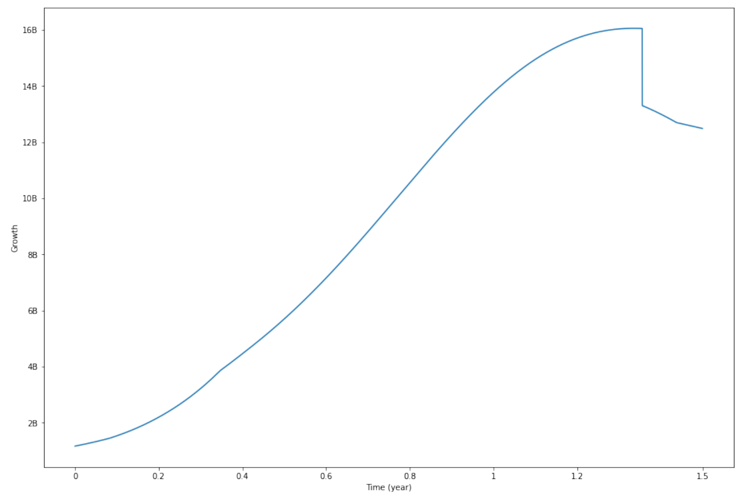

Figure 32: The simulated growth of the number of DAI in circulation for 1.5 years

of the coin trading. Doing this we could move on with modeling, but there is another thing we should take into account. RAI started trading in April 2021, so we do not have exactly the same data. It also had some other issues with peg and other things at the beginning, so it might not be completely representative. This is why we can see relatively strange movement at the beginning in figure 27. So, we also show how it is if we only simulated from half a year on and compare it to the overall growth of RAI Reflex. We show that we might not hit the same growth in that time frame, but this is because we didn't capture the initial growth, from which it then declined. Initial value of the tokens was actually the highest and then it quickly dropped due to the problems they had. Since June 2021 it then increased again almost 4-fold. We did not manage to replicate the problems they had at the beginning because that would have to make us alter the input parameters, which in our case are just constant. Anyhow, once their network was more stable (June 2021), we could better model it. Our model too had similar, maybe even a bit faster growth until it collapsed in a similar way they collapsed. So, we have reasonably similar results. Our results are available in figures 33 and 34.

4.2.2.3 FRAX growth

FRAX was an algorithmic stablecoin, which enjoyed quite a bit of hype between September 2021 and February 2022. We set the returns one could get with staking at 2% higher than the market, collateral at 0.8 (it is not fully collateralized), 5% of the users have it staked for longer term and we adjust the usage (hype) parameter. While FRAX enjoyed a substantial hype for it's size, the highest was between between 9th and 13th month. So, we manually adjust

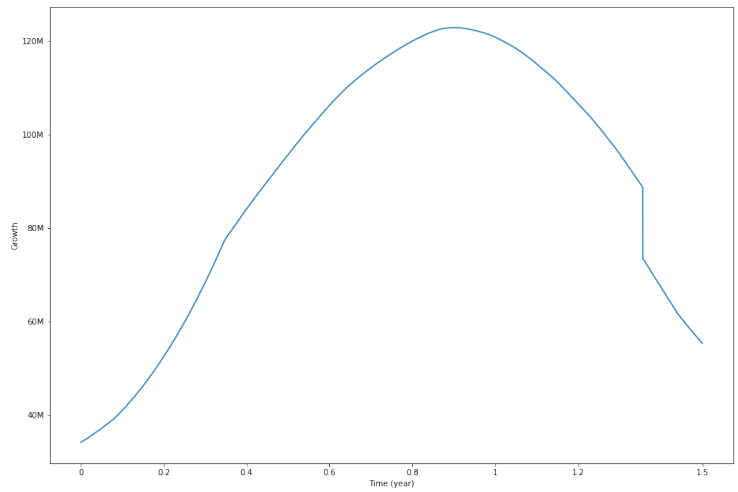

Figure 33: The simulated growth of the number of RAI in circulation for 1.5 years

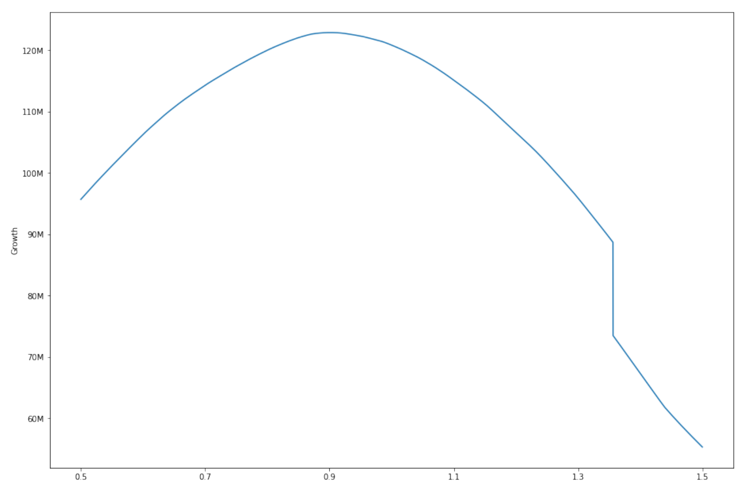

Figure 34: The simulated growth of the number of RAI in circulation for 1 year (from 0.5 to 1.5 years in the future)

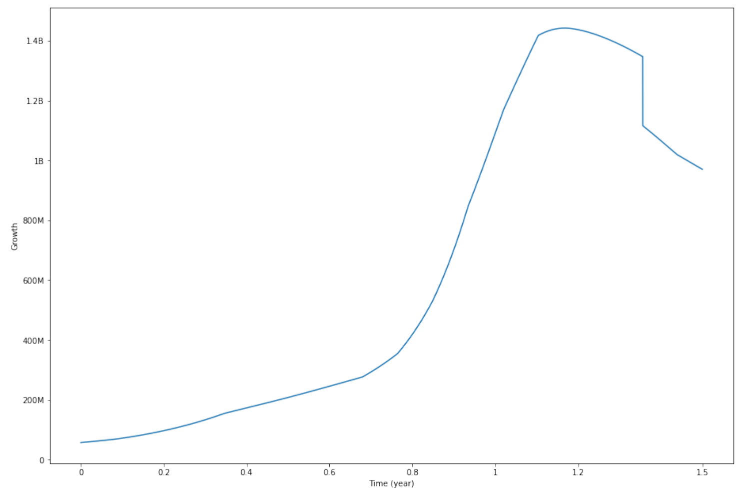

Figure 35: The simulated growth of the number of FRAX in circulation for 1.5 years

the hype to 0.4, .7, .8, .55, .4 for those months (we assume gradual increase and then gradual decrease of the hype). Furthermore, in other months the hype was at 12% since they were benefiting heavily from being uniquely positioned in the market. Our results show similar, albeit a bit smaller growth than the one that actually happened. We started with 57.5 million tokens and ascended all the way up to 1.4 billion, while the actual number was at around 2.9 billion. Again, we do not have the parameters exactly right, but we still managed to capture most of the growth and even the drop of value once it happened in May 2022 relatively accurately. We can see the simulated growth in figure 35.

4.2.2.4 USDP growth

USDP had the same staking rate as other market coins and did not really have any hype (so we set it to 0). Around 5% of the money is assumed to be locked in staking and similar ways and since they are fully collateralized, we assume collateral of 1 over the whole time period. We started at around 335 million tokens and got to a high of around 1.4 billion - very similar to the actual numbers presented in figure 29. We then have a slightly higher decrease than it actually happened. But this coin does not have a transparent burning, so it is possible that they did in fact buy back more coins, but didn't burn them officially, making our numbers closer to the real world. This is especially true because in their numbers that we got from Coingecko there was not a big drop between May 10th and 12th 2022, when UST situation happened (and it affected almost all other coins). Our results are displayed in figure 36.

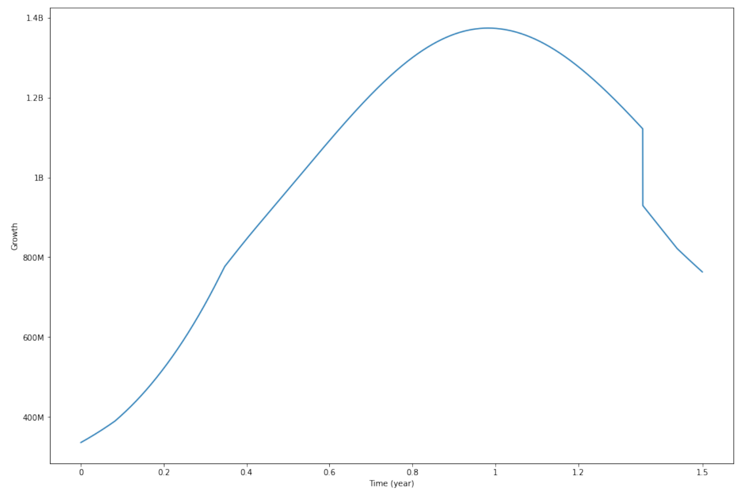

Figure 36: The simulated growth of the number of USDP in circulation for 1.5 years

4.2.2.5 TUSD growth

TUSD had according to our observations (we observed current staking returns in June 2022) quite good staking returns, so we set them to 2% above the market rate. We assumed very weak hype (it did have some minor hype in the first half of 2021) at 1%, 5% of the money is assumed to be locked in staking and similar ways and they are fully collateralized, setting their collateral ratio to 1. It started with 281 million tokens in circulation and it grew up to around 1.6 billion in actual data and 1.4 billion in our simulation, which is again quite close to reality. Our results show a bigger drop of value than it happened once the market conditions got worse - but again we would warn here that their burning process is not completely transparent either. So, it is possible that we might have not missed those values by much. We display the actual values in figure 30 and simulated in figure 37.

4.2.2.6 Conclusion

We made some fittings of our parameters (mostly constants in the model) in order to get the values just right for our simulation. We did this without taking into account for the volatility. We do set volatility relatively low and keep it independent from network growth in order to not lose the expected values too much and because we already have volatility from other variables in our equation.

In the end, we chose the following constants in our model (to get the results described above):

$M = 2.6$

$C_i = 2$

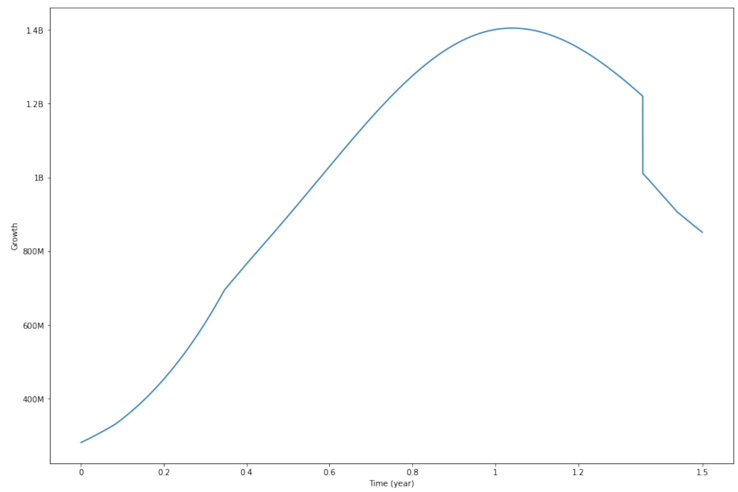

Figure 37: The simulated growth of the number of TUSD in circulation for 1.5 years

$C_{dep} = 5$
$C_{us} = 5.2$
$C_{msent} = 1.05$

4.3 Our model

In previous section we have fitted the parameters for our model. We still have some processes and parameters that we still have to fit, but our goal is now to simulate the same model for 5 years in the future with the assumptions that our model is taking. So, we add additional parameters: $\sigma_{us} = 1$
$\sigma_G = 1$

Furthermore, we have set up the constant that determines the power of market sentiment to 1.05. This was due to strong growth of stablecoins with the market. While such growth is possible to last in the future, we believe that we should be cautious and expect a smaller growth. The reasons are that central banks might decide to compete with their stablecoins and that the market will consolidate at some point and it won't only grow with cryptocurrency market, but with the utilities that those stablecoins provide. Those utilities are then better explained with other parameters anyway. So in order to be cautious we have decided to reduce this parameter to 0.55, which caused us to have smaller growth in our simulation. What is more, we do not want to rely on hype, so we set the hype to 0 and let it be volatile, which would represent different market sentiment on us as the time goes on.

Another parameter that we have to set (that we did not have to set before when fitting the model) is the starting amount of tokens that we have among our community. Note that this is chosen based on our predictions. FRAX started with around 57 million tokens in the end of 2020, which offers a good reference point to us. However, we decide to estimate the beginning number to somewhere between \$20 and \$30 millions for prudent sake given a more sluggish market context at the moment. This is in our opinion achievable and realistic. In our model we make this number uniform random, so each run we pick a number between those two bounds.

We also had a shock on May 10th among most, if not all of the stablecoins. LUNA lost its peg and shook up the cryptocurrency stablecoin market as a whole [hea22]. We also want to model such events that bring abnormal volatility for several days into our stablecoin. We do not know when it will happen, but there should always be a probability that it happens. We assume that such an event can happen at anytime at an equal probability. However, in the future we believe that the LUNA collapse will teach users to be careful to only use stablecoins that are well collateralized. Besides that a government regulation is developing in EU and USA (source [Jac22] and [Jea22]) that will enforce stronger rules on stablecoins making such a situation considerably less likely to happen. While we have only one data point in history of cryptocurrency when that happened, there are less such datapoints in real economy. Partially this is because regulation, partially because governments and central banks are well aware of such a scenario and are therefore manipulating the market before that happens, for example by limiting withdrawals like in Greece in 2015 [Lia15] and similar. In cryptocurrency space, it is harder to use such tools, so such events can happen. However, we do not know their exact probability and consequences. Probability of this happening to a major actor (and completely destroying the protocol) is very low, however we set it to 3% per year. It is questionable if this is realistic given that large stablecoins will likely be forced to be revised or will be transparent (like DAI) with their assets is questionable. However we assume such a thing can happen once in 33 years (roughly).

In such a case we use the only data point that we have to model the consequences. At LUNA case, stablecoins such as DAI and FRAX lost between 20 and 40% of their assets in two days (which can also be seen in figures 28 and 26). This is also our p value in the model described before. So, we assume that such an event will last between 20 and 60 hours (that would be our m value in the model) and wipe out 20-40% of our tokens (they would be exchanged for USD). We set boundaries on both variables because we are not sure about the real numbers.

4.3.1 Single path simulation

Below we present and comment one random path in our simulation. In figure 38 we can see how an example of our growth would look like if we assume collateral to be at 0.98, the same deposit rate as the rest of the market, constant 15% of the people staking over the whole time period, hype is modeled as a process with the expected value of 0 (so it has only volatility) and we have index growth in line with the growth of our index (we made an analysis of that before). We can see that for the first two years we endure quite a lot of hardships and even

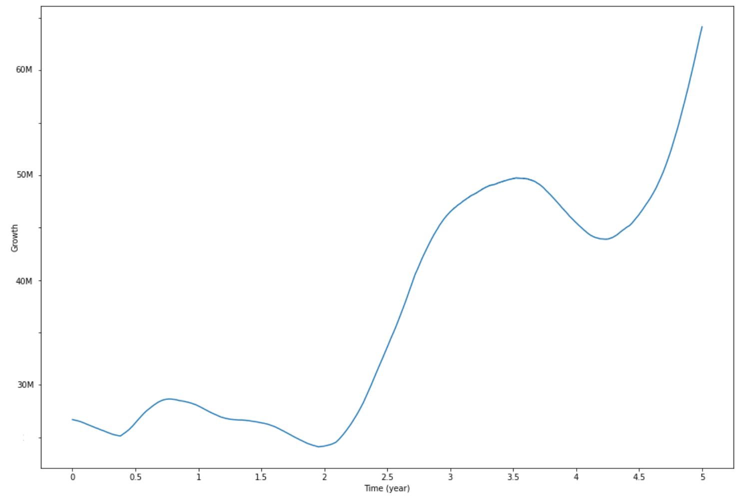

Figure 38: The simulated growth of our network for 5 years in the future for one random path

decreased number of assets under management in the first two years. Market seems to have been bad at that time, but after two years it kicked off and more money started coming in the project. After 5 years we finish with 64.15 million dollars under management. In order to have a better overview of what was causing the growth of the network, we attach the market sentiment graph for that path in figure 40. We can see that it was in large determined by market sentiment, which makes sense because most other parameters were constant. We also attach the growth of the index for this sample path in figure 39. We can see that it has bit weaker effect on the growth of the coin, but the effect is still there. Note that this example is a little biased; something that we fix in the remainder of the document. We were assuming the USD money outflows, while we should have assumed token money outflows and USD money inflows. It still gives an approximation of how the market will react given the set parameters. Also, in the remaineder of the document (except in this section) our incoming parameters for collateral and interest rate will not be constant, but they will be calculated and simulated each time period.

4.3.2 Large scale simulation

In order to further test our model of where the growth can go, we decided to make 10,000 random paths and make a simulation out of that. We looked at the average value that we achieve at any time point and 2.5% of best and worst cases for growth (bounds). The results are displayed in figure 41. We can observe the gradual growth over the 5 years time. In the average scenario we expect to have $235 million of user funds that users will invest in us. The whole worth of the

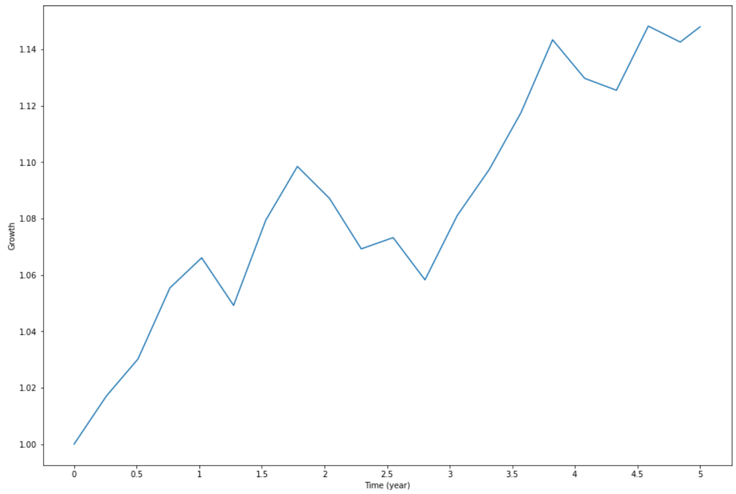

Figure 39: The simulated index growth for 5 years in the future for one random path

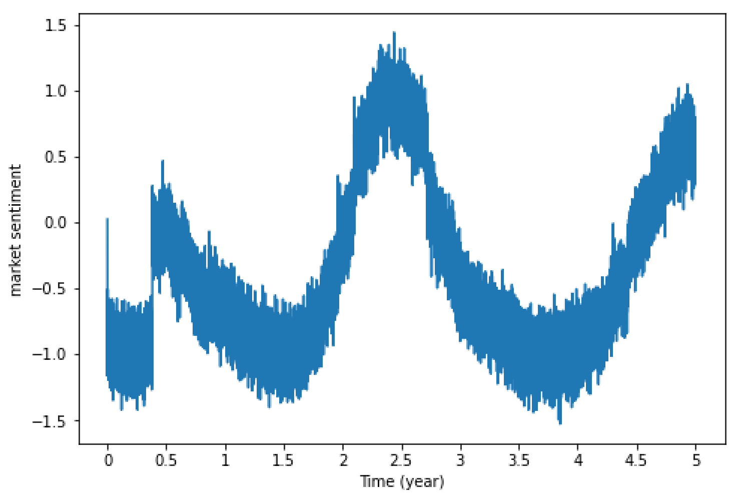

Figure 40: The simulated market sentiment growth for 5 years in the future for one random path

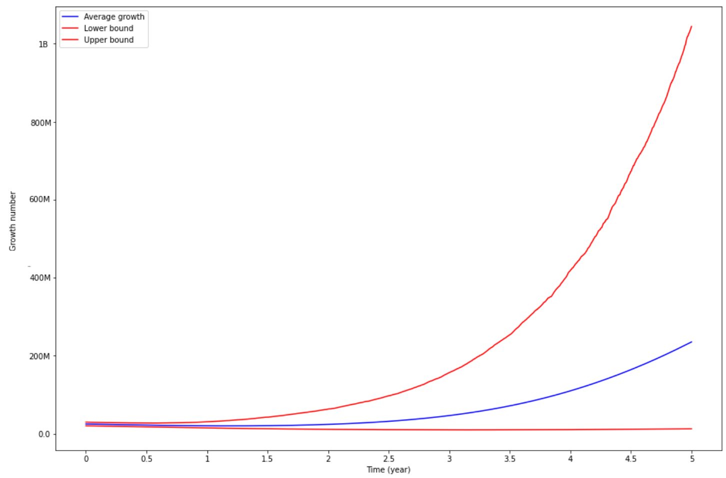

Figure 41: The simulated network growth - looking at avearages and bounds in 10,000 simulated paths

coin will be bigger because they will be added through time when index is likely to also gain value. An interesting result is also the lower bound for our network growth. In such a case we end up with $12.5 million invested from users. This or worse situation happens in 2.5% of the cases.

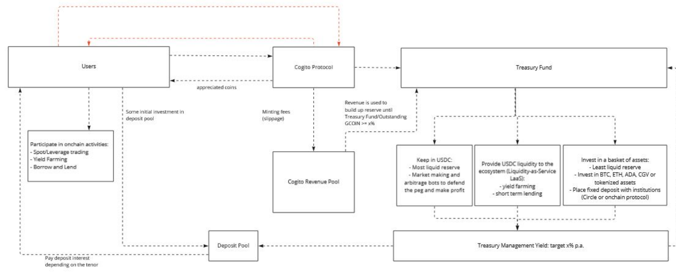

Figure 42: A rough representation of the flow of our assets and liabilities

5 Cogito investment strategy

We have previously described Cogito protocol's network growth, index creation and returns simulation. We now focus on simulating investments, the deposit pool and the liquid reserve.

A recap of how the treasury works is displayed in figure 42. Users pay a minting fee that goes to the revenue pool. The revenue pool gets another income, which is the slippage that we get from hourly trading on DEXs when there is more selling than buying. We now have those assets at the treasury fund and we put them in several different categories. One is **liquid reserve** where we keep the stablecoin reserves, which we can immediately exchange for our coin and maintain its stability if need be. We will also invest that part in liquidity pool to maintain our peg (in financial model at least). The other part of our treasury reserve are our **investments**. We invest a portion of our assets looking for returns. Those returns will then generate more money for us from which we can guarantee the appreciation of the index. Those investments also differ. They can be more or less risky. We will get back to that a bit later in this document. Another portion of our treasury goes to **deposit pool**. This money in the deposit pool then assures money for returns that we can provide in liquidity pool. From there the depositors can then deposit our token and it will appreciate in 1 year time. In exchange they lock the token and are unable to use it for that duration. We will go through those three categories and how we algorithmically rebalance in our model.

5.1 Distribution of money among the assets

When describing the distribution of money among the assets, we first differentiate between starting distribution and all next distributions.

5.1.1 Starting distribution of money among the assets

In our model, we have three incoming constants; $C_{liquid} \geq 0$, $C_{inv} \geq 0$ and $C_{dep} \geq 0$. Note, $C_{liquid} + C_{inv} + C_{dep} = 1$. They represent the share of assets that we target to be in liquid reserve, investments and deposits respectively. Initially we therefore start with a starting capital that we have defined in the growth model. That capital is initially distributed only between liquid reserve and investments. The distribution of that capital in each process is calculated in the following way; For liquid reserve: $Liq_0 = \frac{C_{liquid}}{C_{liquid}+C_{inv}} * A_0$ For investments: $I_0 = \frac{C_{inv}}{C_{liquid}+C_{inv}} * A_0$

Here: A_0 are the assets in time 0. Liq_0 is the liquid reserve at time 0. I_0 is the investment category at time 0.

Deposit pool is assumed to be filled with initial investors in foundation token and with the funds that the foundation initially invests at the begining. They come from the foundation reserve which is dedicated for exactly that. We assume that at the start of the simulation, foundation gives anywhere between 0 and 80% of the share of all the liabilities times C_{dep} (constant telling us the share of money we would otherwise dedicate to deposit pool). So, it gives less than we would otherwise give, but it is still some investment.

Before continuing, we define **Capital Adequacy ratio (CAR)**. This is better defined in our whitepaper, but here we will just briefly describe the accounting. We discount our investments based on their riskiness. Liquid reserve gets a weight of 100, meaning we do not discount it at all. Longer term investments (half a year) will get a weight of 95 meaning that they get 5% discount (while shorter term investments do not get any discounting). This means that if we have 1000 invested in half a year, we count it as 950 assets in CAR. This is because it is locked and has a probability of default. 1 year investments have a weight of 85, meaning 15% discount. Liabilities also have a discount if they are fixed for a long term. We deal with 1 year deposits here and we discount them 12% (weight of 88). So, CAR is basically calculated every time period by dividing discounted assets with discounted liabilities.

5.1.2 Distribution of money with automatic re-balancing

Firstly, we distribute the money at the end of every day. So, we have daily re-balancing. We take a look at how much money we have on hands at that moment. This money comes from liquidity reserve, investments, which give us the returns at that moment (so where duration ends and assets mature on that day) and money that we get from the deposit pool at that day (so that becomes unlocked). Note the money that is there from users buying our tokens (or selling) is located at liquidity reserve. We will call it available money at the end of the day. On the other side we sum up all the liabilities that we have. This is generally just an equation of number of tokens times the price. We proceed in the following way:

1) we first make sure that there is enough money in liquidity reserve, such that $C_{liquid} = \frac{Liq_t}{L_t}$, where L_t are the liabilities at time t. The money comes from available money that we have at the end of the day. If we do not have enough money, we invest all of the available money that we have at the end of the day into liquidity reserve and zero to deposit pool and investments.

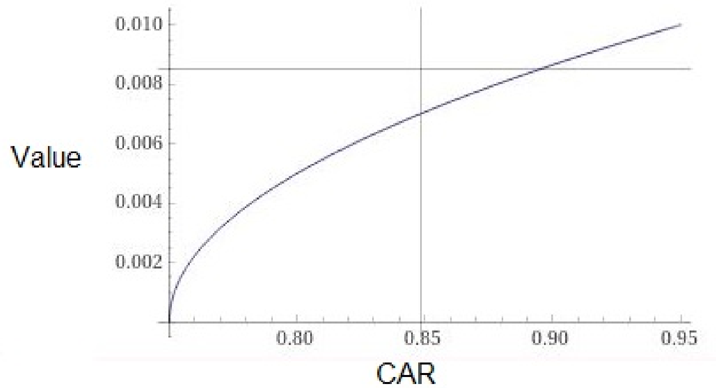

Figure 43: Representation of how the value of the share of money invested in deposit pool decreases with CAR, assuming $C_{dep} = 0.01$

2) After investing the portion (or all) of the available liquidity in liquidity reserve, we are left with a smaller portion (or zero) of the updated available liquidity. We then invest a portion of it to our deposit pool (which we will describe later on). The ideal amount to invest there is $dep_t = A_t * C_{dep} * (1/365)$. This would mean that we invest (ideally) roughly $C_{dep} * 100\%$ of all our assets per year. If we have enough available assets, we then invest in deposit pool. Otherwise we finish investments. This is assuming our $CAR_t > 0.95$. If $0.75 < CAR_t <= 0.95$, then the ideal amount to invest in deposit pool is calculated differently. This is the equation then: $dep_t = A_t * \sqrt{\frac{CAR_t - 0.75}{\frac{0.2}{C_{dep}^2}}} * \frac{1}{365}$. We can see the gradual decline in the investment in deposit pool (assuming $C_{dep} = 0.01$) in figure 43. There only the $\sqrt{\frac{CAR_t - 0.75}{\frac{0.2}{C_{dep}^2}}}$ is plotted. Finally, if our CAR is below 0.75, we do not invest in deposit pool.

3) If we still have available money, we invest it (all) in investments.

5.1.3 Defence mechanisms

CAR is a ratio that makes us guide the investment decisions. But it is more than that if we have a low value of CAR_t. If the value is below 75% at time t, then we stop investing in deposit pool. Furthermore, all the future returns that the depositors should get are halted until CAR resumes to above 75%. If it is below 60%, our index no longer appreciates (but it can depreciate). In that case and also the users assume that the index cannot grow (but it can drop in value). So, when calculating future values, they always assume that there would be a minimum that happens in that time. While in the real world we might discuss of possibly setting another defence mechanism when CAR_t drops below 0.5, we will mark this as a problematic case. This might not be a default, but we do consider it risky enough to point out that our design is in trouble at that time.

In the future versions we plan to dive deeper into that data in order to see how low can we go before we would have to completely lose the peg to our index. For now we will just analyze in how many cases we reached that point.

5.2 Investment pool

Once we have determined the amount of money that comes to the investment pool, we start distributing this money among the different investments. Firstly, as described at the simulation of financial returns, we distribute investment pools in three parts. One is a low risk pool, where there is a low probability of default and low returns. Then there is a medium risk return pool, where the probability of default is slightly higher, but the returns are also a bit higher. Finally, there is high risk pool with the biggest probability of default and highest returns. We invest a portion of all of our investments in each one of those pools. At the beginning (at time 0), we invest equally in all of the pools (so 1/3rd of our investments in each pool). But after that we follow the automated investment strategy. We define C_{lrisk}, C_{mrisk}, C_{hrisk} as the amount of the investments that go to low risk, medium risk and high risk pools respectively. They satisfy the equation: $C_{lrisk} + C_{mrisk} + C_{hrisk} = 1$. However, we have different constants depending on CAR_t. This means that we rebalance differently depending on the health of our collateral. In our case, if $CAR_t > 1.1$, then we invest more in risky assets, so:

$C_{lrisk} = 0.3$,
$C_{mrisk} = 0.5$,
$C_{hrisk} = 0.2$

If $CAR_t > 0.95$ and $CAR_t <= 1.1$:
$C_{lrisk} = 0.45$,
$C_{mrisk} = 0.35$,
$C_{hrisk} = 0.2$

Otherwise ($CAR_t <= 0.95$), we invest in the following way:
$C_{lrisk} = 0.5$,
$C_{mrisk} = 0.35$,
$C_{hrisk} = 0.15$

Furthemore, we then assume different investment durations. Currently there are a lot of available staking pools on the market where we can invest for any time period. This means that we can take profit any time we want. However, there are also pools where we stake for a specific period of time. So, the market is quite complex here. In order to simplify it, we assume that we can invest and lock assets for a day, three months, half a year and a year of time. We have the option to distribute investments for different durations here, however we assume to distribute them equally in each duration. Each investment is then locked for that time and we cannot retrieve it.

We then update investments every time point dt (which is 1 hour time difference). Once the investments mature, we get a payment that gets added to the available money that we have at the end of the day. So, we can invest that money appropriately again. For CAR formula, daily and three month investments are discounted at 0%, half a year at 5% and yearly at 15%. Note, if in time t a hack happens in one investment pool (low, medium or high risk), all durations in that pool lose a certain amount of assets at that time point. This has immediate effect on our accounting and it soon follows that we have smaller payouts, which affects the re-balancing.

5.3 Deposit pool

One of the most important things about our system is also a deposit pool. Each day we invest a certain amount of money in deposit pool. We described how much we invested in previous subsections, here we will focus what happens with that money. Independently of our investment in deposit pool, we model the interest rate for deposit pool. Note, people can only invest in deposit pool for one year. We model it in the following way:

$$deprate_t = max(midr_t - a_t, C_{minrate}) + C_{riskpremium} + \sigma_{deprate} * dW_t^{deprate} * \sqrt{deprate_{t-1}} \quad (3)$$

where:

$deprate_t$ is the deposit rate at time t.

$midr_t$ is a staking rate for medium risk investments.

a_t is the expected appreciation of the index in one year time (at time t). Assuming we do not change it due to the poor performance of the assets we assume to know the exact values for the future. In case we have low performance, users expect to be worth the minimum amount that it would otherwise have in a year time.

$C_{minrate}$ is the minimum rate that we still have. We do not allow very low or zero interest on our deposits in our model because we prefer to err on the side of caution. Our default value is 0.005.

$C_{riskpremium}$ is the risk premium the market assumes on our deposit pool. Given that they lock the tokens for 1 year, we assumed the constant value of 0.025.

$\sigma_{deprate}$ is the constant that adds to the volatility of our deposit rate.

$dW_t^{deprate}$ is a random process that is modeled using Student-t distribution with 5 degrees of freedom.

Here we therefore assume we will constantly have positive (and quite a bit above 0%) deposit rate. This is not because we do not allow for close to zero or even negative deposit rates in practice, but rather because we prefer to err on the side of caution (since we will have to pay for those returns). We also compare our investment to the medium risk investments and add some additional risk and risk premium on top of it.

Once the deposit rate is set, we then have the money that is meant to be assuring the returns. If for example deposit rate is 5% and there is $1000 worth of tokens deposited, we had to invest 50 in the deposit pool to assure this appreciation. The amount of money coming in deposit pool was described before. What we still need is to define how this money will be used. We use the following equation:

$$d_t = max(min(C_{daily_{red}} + C_{daily_{red}} * \sigma_{red} * dW_t^{reps}, 1), 0) * \frac{1}{24}$$

Here:

d_t is the share of assets in our deposit pool that will be reduced in time t.

C_{daily_red} is the constant, which determines the drainage of our deposit pool. In our example it is set to 0.25.

dW_t^{reps} is a random process that is modeled using Student-t distribution with 5 degrees of freedom.

Using this setup, we can expect that in the long run we will lose around 25% of the summed value of the assets invested for depositors per day. This means that we will usually have some small portion of assets in our deposit pool that are unused. However, that portion proves to be quite small over the time.

Given d_t, we can then calculate the amount of tokens deposited in time t. We simply divide the amount of deposits we invested multiplied by d_t with deposit rate. This is then the amount in time t. At that time we also decrease the money that we have currently invested in deposit pool for that amount. What we do next is that we save those hourly amounts and every time period t we then multiply them by the same number - deposit rate that we had at the time of investment times dt. After one year the users therefore get the tokens back and our invested assets that covered the interest rate increase are released back to our assets in form of liquidity reserve. Note that the assets that we invested in deposit pool returns are not used in the calculation of CAR_t (or collateral ratio) nor are they invested anywhere. We get them back after a year and that's when they come back into the calculation of our assets. At the same time we also add the number of tokens in circulation at that time for the amount of tokens that the user has gained by the appreciation of the token due to depositing. So then after a year our newly generated tokens are covered by the money we invested in deposit pool.

When our CAR_t falls below 75%, we also stop investing in deposit pool. But there might be some existing investment already and we are still enabling returns from this existing investment until it dries up. Furhermore, we no longer update deposit returns if $CAR_t < 0.75$. This means that if CAR_t drops, we freeze returns in a similar way as we freeze index if CAR_t drops too much.

5.4 Other calculations

Every time period t we also calculate the collateral, which is just summed assets (liquid reserve and investments) divided by liabilities (which are the number of tokens times the price). Note, if a user depsited 100 tokens at 5% interest rate, we calculate that as 100 tokens in liabilities all the time until the time of the redemption (after 1 year). But that's when we add the assets which we added to guarantee the deposits, which should match the return minus the appreciation of the index (so we get 5 tokens to our liabilities and 5 tokens at the price that was set a year ago worth of USD to assets). Furthermore, we calculate in each period different statistics about our deposit pool, such as the amount deposited, percentage deposited compared to all tokens and USD amount (so amount of assets) that is used to guarantee the returns to depositors.

We also calculate slippage every time period. We assume that we have put all of our liquidity reserve into the pools and we follow the Uniswap V2 formula. With this we calculate the slippage each period. Each period we then re-balance the deposit pool in such a way that we keep the same price. So, if there was a buying of the assets beforehand (in previous time period), then we add our tokens on the sell side to keep the peg (because we just got more assets to our liquidity reserve). On the other hand, if they were selling, we had to buy more using USDx coin and therefore we have lower price, so we re-balance by taking away some of our tokens. Every day we then get a new liquidity reserve, so we calculate the peg based on new liquidity reserve and we set just enough tokens to keep it. In case that our liquidity reserve reaches 2% (for example in an event of a massive run on our tokens), we stop maintaining the peg on our token until our liquidity reserve improves. That is until when the liquidity from investments comes back to liquidity pool. We keep the same amount of our tokens in Uniswap pool and let the liquidity pool dry up, but we don't change the amount of tokens we hold at the pool. The liqudity pool then changes itself through the rebalancing and users selling and buying the token. In such a case we could experience negative slippage for a short period of time.

The foundation gets the slippage income in case when price is too high, that is when users buy more than sell. When it is the other way around, the slippage goes to the treasury of our token.

In case our CAR_t is above 1.1 at the end of the year, we take 1% of our assets (calculated as liquidity reserve plus investments) and add them to the foundation. We take it from the current liquidity reserve.

We also calculate the number of tokens in circulation in every period. However, this is not directly connected to growth modeling. When we were estimating the parameters, we did it for stablecoins that keep the same peg to their pegged assets. We keep it to the index, which is slightly different. The new incoming money that is calculated in growth modeling goes in USD. They are then exchanged to tokens using the exchange rate that we have. When there are outflows from growth modeling, users are selling the tokens according to our exchange rate to USD.

5.5 Second strategy - riskier strategy that targets higher return

We are also interested if we can achieve higher returns (and with that assume higher average index growth) using a more risky strategy of investment. Such a strategy is riskier, so it will not work as often as the strategy described above. This means that CAR_t would drop below 50% in time t more often, which we consider problematic. This could be risky in because we are considerably more likely to experience a coin run due to bad collaterization.

In this strategy, we only invest 15% in liqudity reserve and 0.2% in deposit pool. We therefore have significantly less depositors and liquidity reserve. We set $C_{liquid} = 0.15$, $C_{dep} = 0.002$ and $C_{inv} = 0.848$. This means that we invest considerably more in our investments compared to lower risk strategy we described above. At the sam time we invest less in liquid reserve and deposit pool, making a much weaker stabilization for our coin. We keep the same definition of our CAR and calculate it in the same way. Defence mechanisms are the same as well. The rules for deposit pool and the investments there are the same as well. We do however change the investment strategy slightly. We still invest 25% among different durations, but we do change the distribution of our investments over the different risk pools. We then invest based on the following strategy:

If $CAR_t > 1.1$:
$C_{lrisk} = 0.2$,
$C_{mrisk} = 0.3$
$C_{hrisk} = 0.5$
If $CAR_t > 0.95$ and $CAR_t <= 1.1$:
$C_{lrisk} = 0.33$,
$C_{mrisk} = 0.34$,
$C_{hrisk} = 0.33$
Otherwise ($CAR_t <= 0.95$), we invest in the following way:
$C_{lrisk} = 0.45$,
$C_{mrisk} = 0.35$,
$C_{hrisk} = 0.2$

We invest one third in each asset in time 0, similar as for lower risk investments. We also made a simulation with this strategy, but we were trying to match a higher average index growth in such case.

6 Results

Here we will discuss the results. Our default results hold for a simulation where we assumed roughly 1.2% average index appreciation per year, default settings for growth and probability of default, where we invest 1% of the assets in deposit pool, 25% in liquidity reserve and the rest (74%) in investments. Below we will present the results and explain them. Note, that in the results section we simulate all the sections before. We simulate index growth, returns from staking, growth and apply our strategy. We then display our results of this in this section. Note, we calculate CAR_t values every time period t (which is different than in section 4 where we assumed constant numbers). The share of stakers is no longer constant but it changes with time as explained in section 5.

6.1 Single path simulation

We made a single path just for a display of how different processes interact with each other. We also made a Monte Carlo simulation to assess risks. In figure 4 we can see the returns of different investment pools. There was a sharp drop in high risk return pool around 0.8 years into the future. This is when a hack or default event happened and a big portion of our funds that were invested there were compromised. In figure 5 we can see how our returns were changing over time. They were quite volatile, but usually high risk pool offered the highest returns, sometimes exceeding 9%, which is similar to what happened in the recent year or so as well. We can see in figure 6 how returns look like in the first month of our simulations. This gives us some overview of daily and even hourly volatility. Just to make sure we check the long term staking return, which only indirectly affects our staking returns. They were described in section 3 and we can see them in figure 7. We can also see the development of market sentiment in figure 8, which in was our specific case quite predictable. Furthermore, the probabilities of default were moving as previously described in section 3 and are shown in figure 9.

We also show how a sample path of a network growth was behaving. The results are shown in figure 44. Note, around year 4 there was a sharp drop in value. This was due to the coin run that would hit us. Note that when network growth changes, we check if it was positive or negative change. If it was positive, we assume buying of our tokens. Most of the time the price of our tokens is different than 1, so the network growth numbers are not the same as the token numbers. Furthermore, when network growth change is negative, we assume selling of our tokens (which again do not necessarily have the price of 1). So network growth does not give us a direct information on the number of tokens or money invested in our coins. We will calculate that using other metrics. Furthermore, there is a probability of a run to our coin calculated within our equations. We made sure to choose a path where such a run happened in order to describe its effects. Note, in most of the runs it did not happen because there is a quite small probability that it happens in a specific simulation.

Also, when discussing coin runs, we are also interested in slippage percentage and how long the users pay for an increased slippage. We can see that in our sample (as displayed in figure 64). In our case the increased slippage that comes due to a bank run lasts for about 5 days or a bit over 120 hours. This means that we fixed those problems in less than a week.

We then go on and calculate the metrics for our own network development in that time. The first one is the liquid reserve over time. We can see it in figure 48. There it is displayed as a share of liquid reserve versus the amount of liabilities. In the beginning and most of the time it was actually just mirroring the network growth. The only difference was around year 4 when the coin run happened. There we briefly lost most of the liquid reserve in order to defend the peg. It then relatively quickly rebounded. We can see a very similar story in figure 47. We only dropped the desired reserve at the time of a coin run and we needed a short time to get the investments from investment pools to recoup the losses. In line with this is also the amount of tokens in circulation that we can see in figure 49. It was initially increasing and then after year 2 it slowly decreased back to the year 3 and then it started increasing from there. There was then a sharp drop due to the coin run around year 4 and then it started increasing again. We ended up with around 85.5 million tokens in circulation. If we have that information (the number of tokens) and the price (which is an appreciation of the index), then we can calculate total liabilities that are displayed in figure 50. They follow the amount of tokens quite closely and they are a bit higher because the price of the token also increases as we can see at the index growth if we take a look at the figure 52. Our index increased in price to around 1.11 in year 2.5 and then within the year after that went back to 1.04. While we will try to prevent such high drops, this is possible in the current configuration of the index.

Higher index (and with that price) growth reduces the collateral, which is shown in figure 51. While it is quite important on price growth, we can also see a sharp drop around 0.8 years into the future due to the default of one of the protocols we were investing in. We can see that after 2.5 years the collateral was increasing again because the index was falling. At the time of a coin run, we get increased revenues due to slippage, which is caused by overselling our tokens. This gives adds additional revenue and therefore pushes the collateral back up. At the end of the increase of collateral we also get a bit of a drop due to the fact that after a coin run there might have been some discount on our coin due to the loss of a peg, so we lose some collateral. Furthermore, we started investing back in deposit pool, which makes it hard to keep high collateral.

Figure 53 shows the investments over time. They follow liquidity reserve and overall growth quite well. Towards the end we had some changes of deposited USD for deposits, as we will see later on. Figures 54, 55 and 56 show how many assets we have in low risk, medium risk and high risk pool. We can see quite a lot of rebalancing in the first year (especially in high risk pool). This is because we start with the same distribution in every risk pool, but then we have rebalancing of the assets right after that and as soon as our initial investments mature. Rebalancing is especially apparent in high risk investments because we generally invest less in them. Furthermore, we can see it was additionally hurt by the default in around year 0.8. We also had a shock around year 4, which cause quite a big drop in invested assets.

In figure 57, we can see the number of deposited tokens (that the users deposit in our deposit pool). At the beginning we get a boost from foundation for deposited tokens, so initial growth is slow. After 1 year we can expect somewhat of a stop, but we continue to grow because most of our network grows anyway. Then it eases up a bit after year two and starts growing with the network again after year 3. Even the liquidity shock only temporarily hurts deposited tokens. This is because they are deposited for one year and after the end of the shock we start with investments in deposit pool again anyway. We see another interesting phenomena when we look at the share of deposited tokens versus all the tokens in circulation, displayed in figure 58. At the beginning the share of deposited tokens is growing fast, but it then slowls down as the network eases fast growth and it then starts decreasing. We do not find a perfect balance between the money we need to deposit in the deposit pool (shown in figure 59) and some stable long term average of deposit pool. But that is ok, since even though the amount of tokens in deposit pool is decreasing, it still stays high in the long run. A share of USD invested in deposit pool versus all the assets that we had is shown in figure 60. As expected, there we decrease the amount of USD deposited after first year, but it is then increasing when our finances are good. We get additional decrease before the coin run, but sudden increase right after the coin run. Sudden increases after a coin run likely happen because after it we start getting enough liquidity again and in general our financial situation improves quite a bit. So we get back quite some investments in deposit pool. In general this share is reasonably stable, at least when we do not have major shocks in our system. There is another relation between the amount we deposit in deposit pool and deposit interest rate, shown in figure 62. We can see that it is very volatile and that it often hits the minimum that we assumed to be around 3% due to a risk premium. We assume that users will always want at least some deposit rate, though as this path shows, sometimes they might be happy with very low or even negative rates (though such periods probably won't last long in most cases).

A very important internal metric based on which we take decisions is capital adequacy ratio (CAR). We take a strict action to avoid problematic financial situation in case CAR is low and CAR over time in our path is shown in figure 61. Note, it has some big jumps when our assets mature and we discount them differently. An asset that is staked for a year has a big discount rate, but once it is moved to liquidity reserve, it no longer has a discount. We see that CAR ratio is most of the time a bit smaller than collateral ratio and it has quite a lot of jumps at the beginning when we rebalance a lot. We can also observe a drop around year 0.8 when a portion of our invested assets defaulted, as shown in figure 4. It went quite a bit down when we had quick price growth, but it recoverd a great deal when the index went back down. During the coin run it gained a lot again, as expected and then had some correction since we had a very strong coin run, which resulted in us temporarily having less than 2% of liquidity reserve; therefore we temporarily dropped a peg to our coin. So

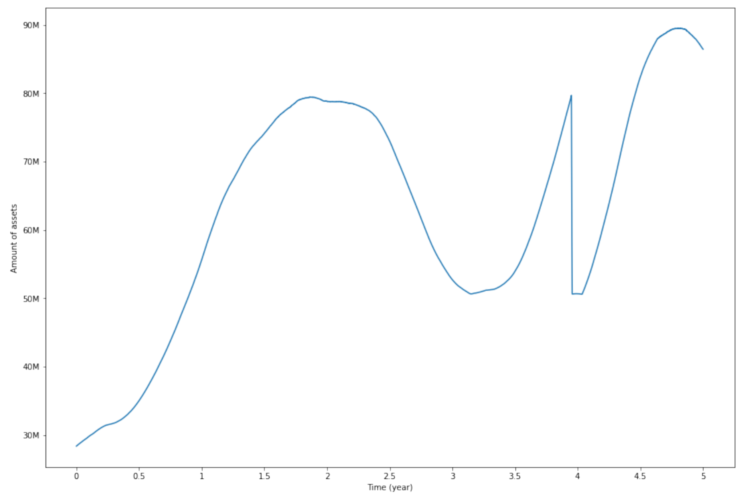

Figure 44: A sample path showing the network growth over time

on the way back it was possible to buy a token at a discount. It then slightly decreased due to increased investment in our coin (which drags it towards 0.95 and collateral towards 1) and finished a bit above 1.

Finally, we display our revenue for the foundation in figure 63. We expect low revenue at the beginning that then increases due to fast initial growth of our network. On the third year the revenue decreases again, but then it gets better afterwards when we have more growth again. Note that this comes from slippage. We will try to reduce some slippage in Uniswap V3 pools once it is available, but we do not expect a major decrease in revenue since it can happen that we invest in more than one pool or have a higher bounds for the price difference. We can see that the foundation gets a lot of slippage right after the coin run, that happened before year 4. This is shown in figure 45. This is because we have very few tokens in liquidity reserve and even after the coin run, there can be a quite high slippage to be paid on the demand side. Even bigger slippage is received by our treasury, as shown in figure 46. At the times around the bank run, people often act erratically and make the decisions that are financially not the best due to the fear that the projects might fail (especially in the case when we get back to the peg). They therefore pay quite a lot of slippage, which is then going mostly to the treasury.

6.2 Monte Carlo simulation

We also made a bigger simulation with 10,000 runs and looked at several metrics and analyzed them. We took the same assumptions as for one path simulation described before. Here we explain the results.

We already saw the Monte Carlo simulation for returns in section 3. Here we first look at the network growth. In figure 65 we can see that we will grow

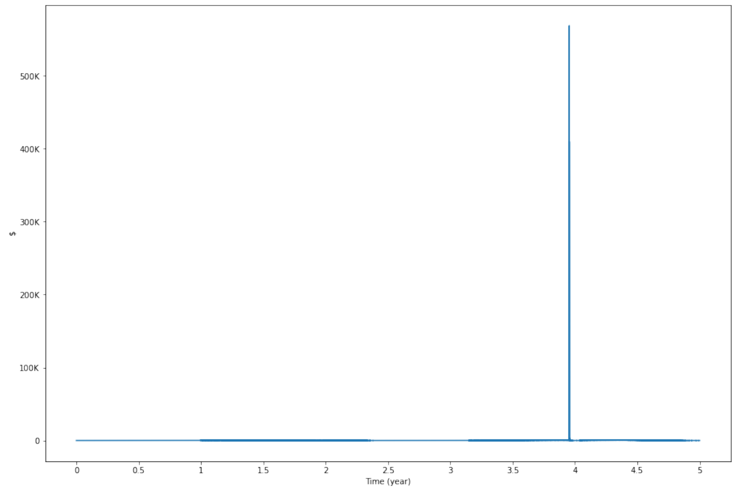

Figure 45: A sample path showing the slippage income that foundation gets over time

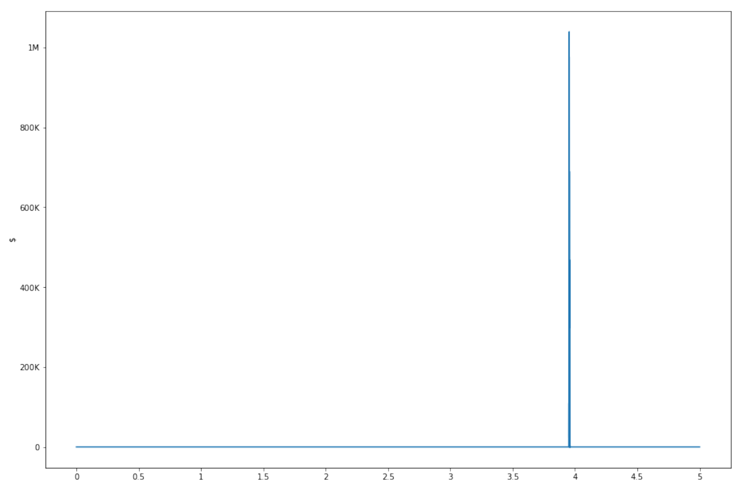

Figure 46: A sample path showing the slippage income that the coin's treasury gets over time

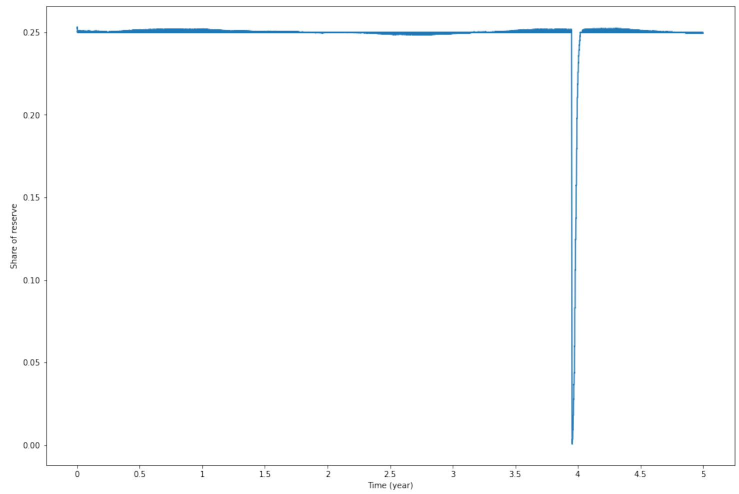

Figure 47: A sample path showing the share of the liquidity reserve over time

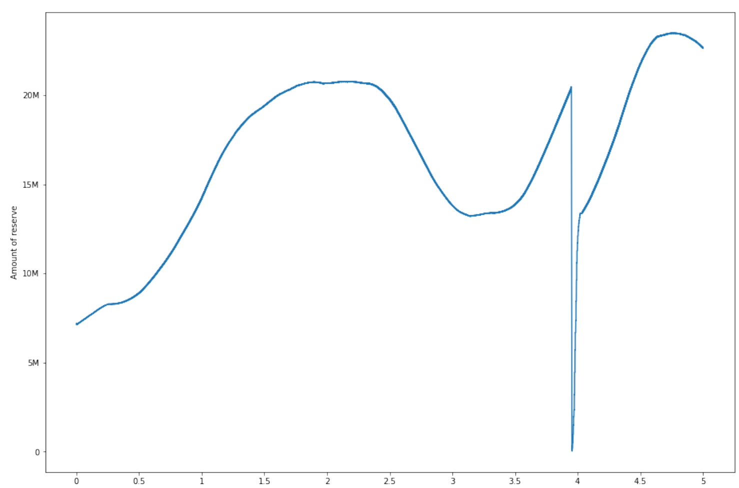

Figure 48: A sample path showing absolute amount of money in liquidity reserve over time

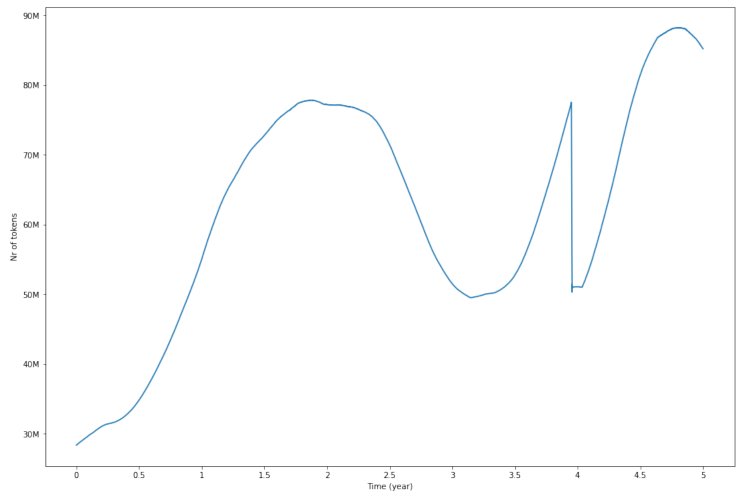

Figure 49: A sample path showing the number of tokens in circulation

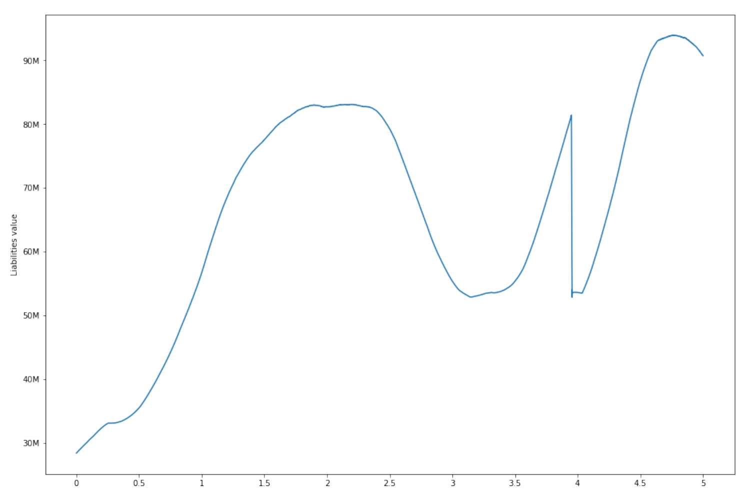

Figure 50: A sample path showing the total amount of liabilities over time

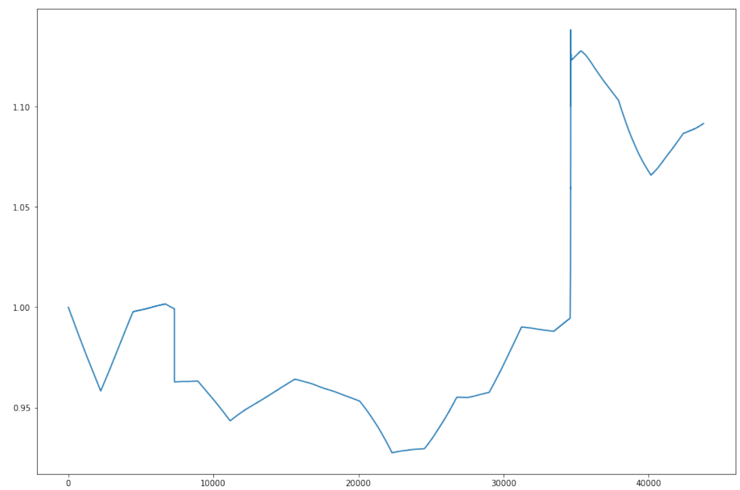

Figure 51: A sample path showing the share of collateral over time

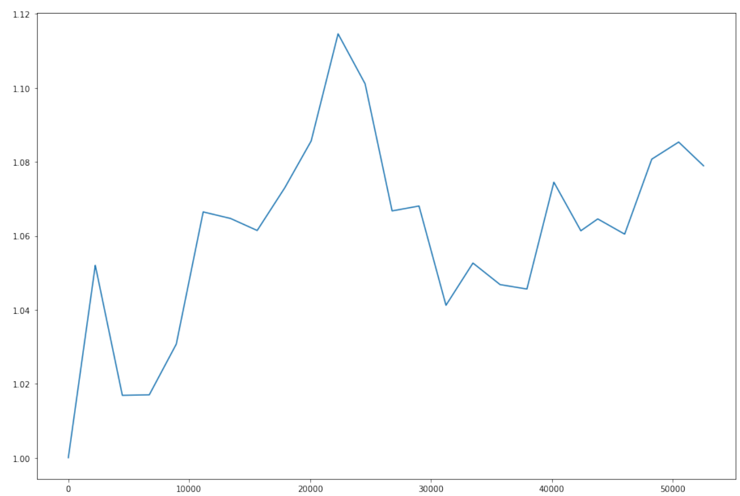

Figure 52: A sample path showing the price development over time

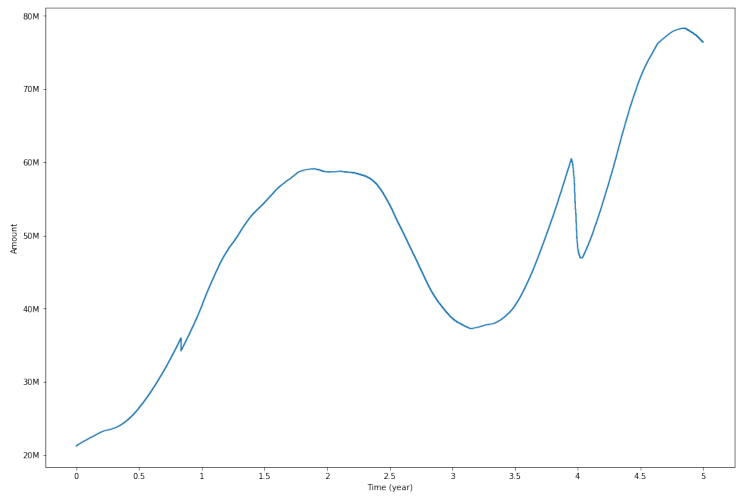

Figure 53: A sample path showing the total investments over time

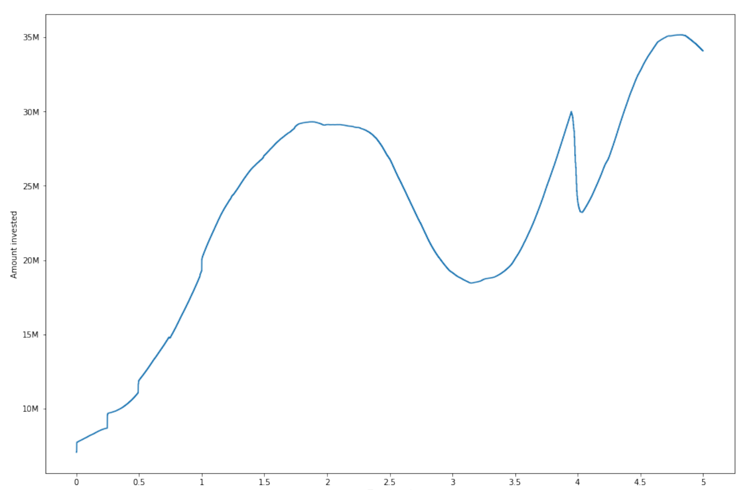

Figure 54: A sample path showing the total amount invested in low risk investment over time

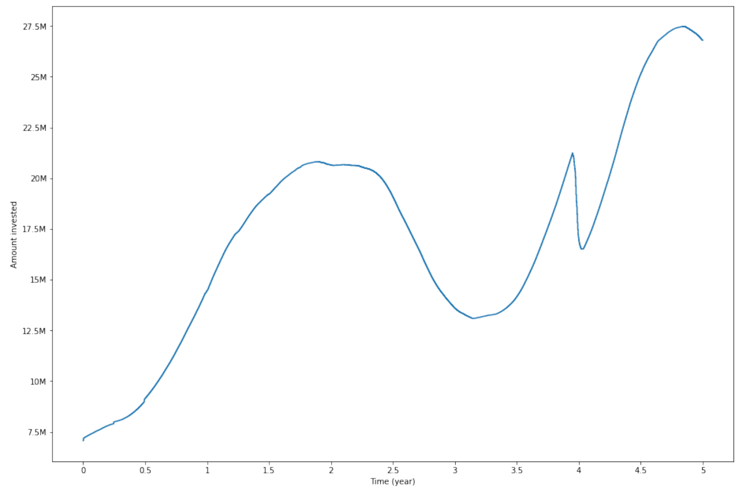

Figure 55: A sample path showing the total amount invested in medium risk investment over time

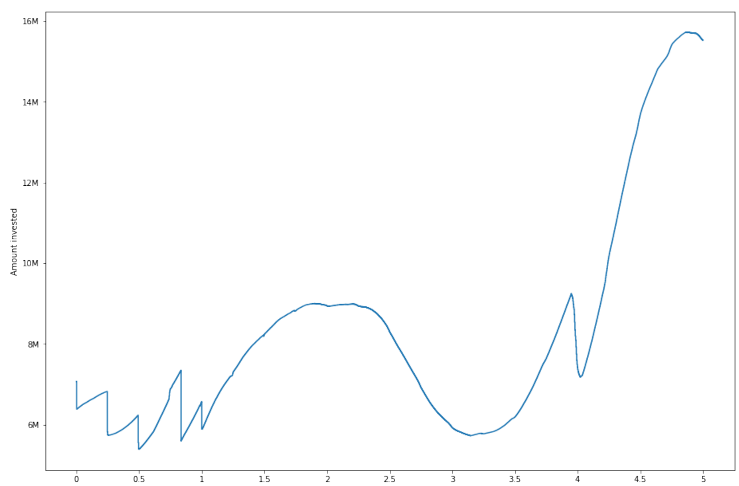

Figure 56: A sample path showing the total amount invested in high risk investment over time

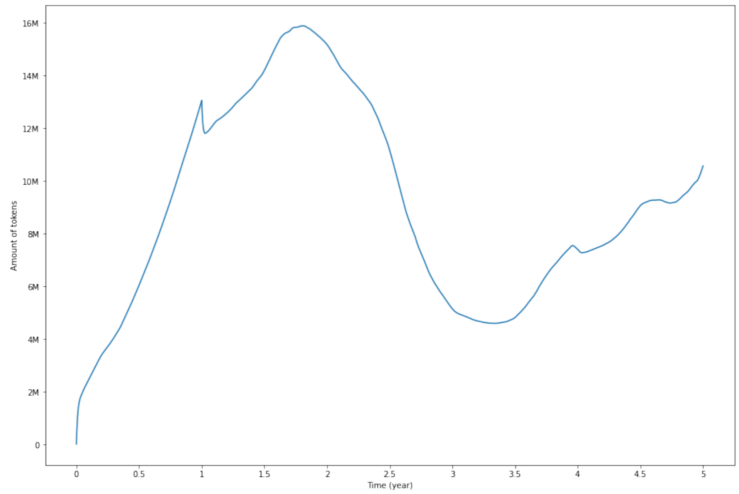

Figure 57: A sample path showing the number of deposited tokens over time

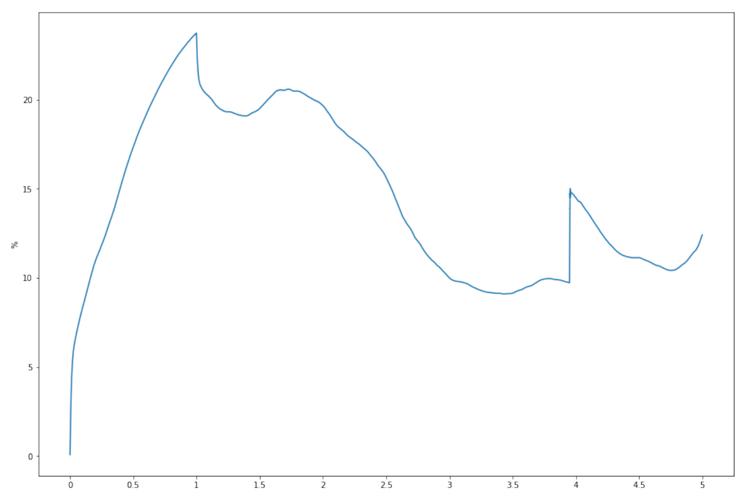

Figure 58: A sample path showing the percentage of deposited tokens over time (percentage versus all tokens in circulation)

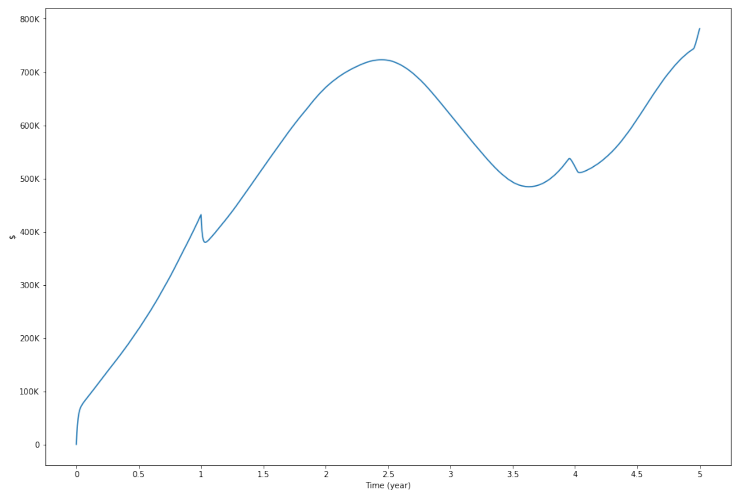

Figure 59: A sample path showing the total amount of USD invested in deposit pool over time

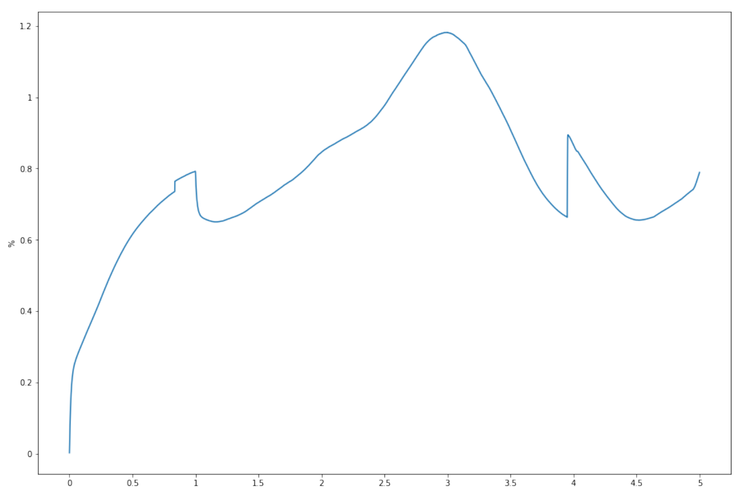

Figure 60: A sample path showing the percentage of deposited USD over time (compared to all the assets that we have)

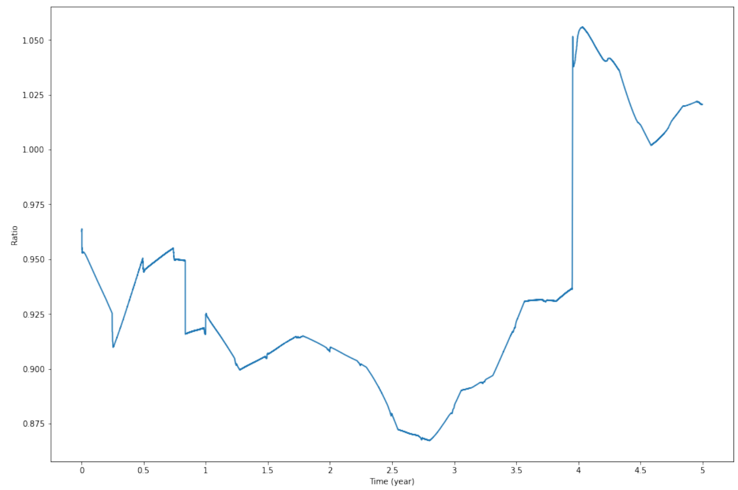

Figure 61: A sample path showing the development of Capital Adequacy Ratio over time

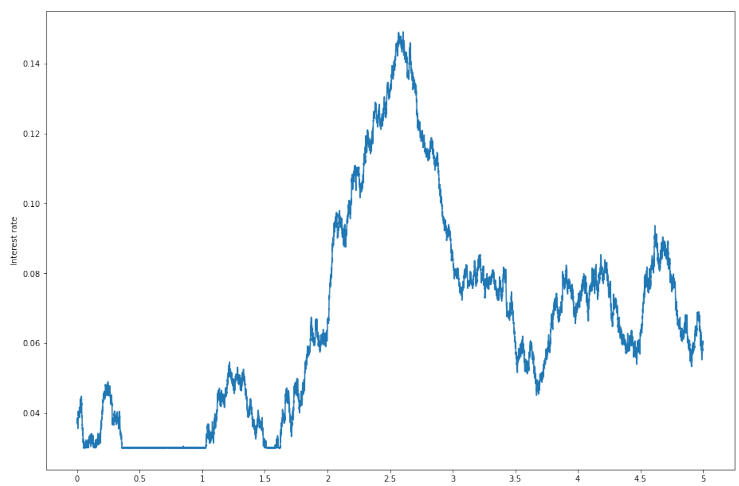

Figure 62: A sample path showing the development of deposit rate over time

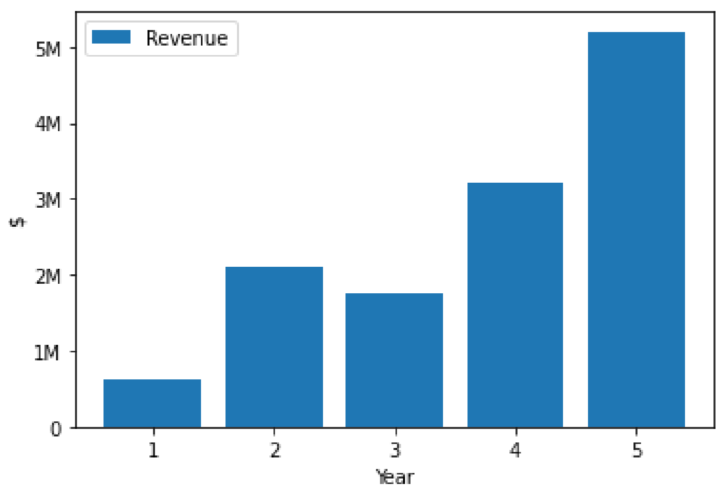

Figure 63: Every year the foundation gets a revenue from slippage and treasury (if CAR is high enough). Theses are the revenues generated in this sample path

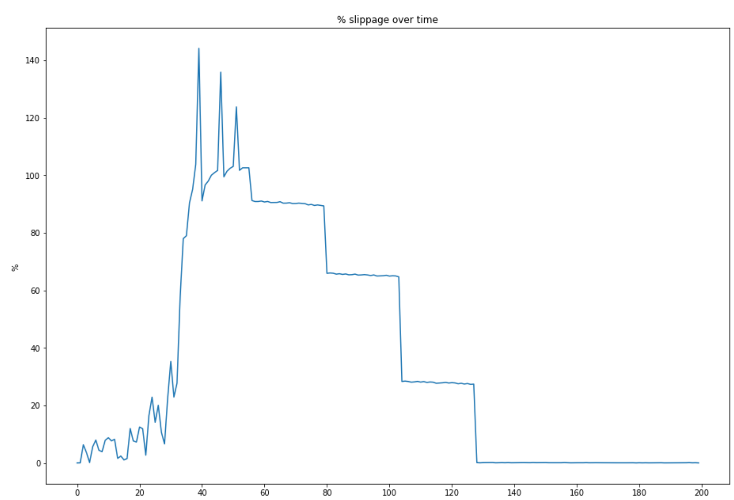

Figure 64: The slippage the users paid when our coin run (and how long it lasted)

roughly 10 times compared to initial value and that we are exposed to quite high upsides and downsides. Due to the latter, we also show the lowest percentiles of growth in figure 66. In 1% of the worst cases our growth might just as well stall and remain roughly the same over the whole time.

We also took a look at the cases when we had coin runs and how they shook up our network. 8.5% of the cases, our fractional reserve fell below 5% and it stayed there for a median amount of 348 hours. Note, we still defended the peg at that level of fractional reserve. We fell below 2% fractional reserve (when we temporarily stop keeping the peg) 6.04% of the times and stayed there for a median time of 141 hours. So, we might lose a peg and stay without at for almost 6 days on average in around 5 % of the runs. We also had over 10% maximum of the slippage payments in around 13.5% of the runs, meaning that in case of a coin run, users will quite often pay above 10% slippage temporarily. The median amount of hours it stayed that way was 6. So in general our slippage did not stay that high for long.

Next, we look at the liquid reserve. We can see in figure 69 how the liquid reserve behaves over time. We can see that the absolute numbers are quite stable over time except maybe at the beginning. There we can see that in the lower bound we have quite a few problems, which are better seen in figure 67. There we can see that the first two years we have a hard time keeping the fractional reserve at 25% stability over the whole period. Later the system becomes more stable and we are better prepared for shocks. The explanation of why such things happen would be due to the fact that at the beginning we invest most of our assets and we often assumed that we start in a bad time. That is a time when our network is contracting. So, we do not get much liquidity into our system and people are selling their tokens. We use up initial investments and as a consequence we are waiting until the investments mature, so we can reinvest properly. This gives us some initial liquidity problems (in some paths). This can be even better seen in figure 68. Even in 10th percentile of the worst cases this sometimes happens. In 1% of the worst cases this repeats over the whole period of 5 years, but this is partially also because of the coin runs and defaults that happen while the network is temporarily contracting. However, there is a silver lining here. Firstly, those liquidity issues are not too big, so we will not really lose a peg or have unsustainable slippage because of them. And secondly, at the beginning they happen only when we launch our coin in a bad state of the market. This shows us that we should avoid that, if possible (though we can survive even if we launch it in a bad market).

In line with the liquidity reserve is also the amount of tokens that we have in circulation, displayed in figure 70. We can see that we have relatively gradual increase here to an average value of 293 million tokens and a median value of 192 million tokens. Perhaps more interesting display is a display in figure 71. There it shows that in the lowest percentiles we get a much lower growth and it happens quite often that the growth is also negative at the beginning. Again, this usually happens when we start in bad market conditions. In most of the cases we do expect to start of with less tokens than we end up with except in the most negative 1% of the cases. Another interesting thing is that after an initial decrese there is a small increase in worst cases and then a decrease again. The decrease could happen because of the variety of reasons, such as market cycles or also market shocks (defaults, coin runs) which shake up the stability of our system. A very similar story can bee seen in the growth of liabilities, shown in figure 72. We seem to have quite stable growth there and also when looking at the negative cases, we have no surprises there - as shown in figure 73. Those are intuitively expected results, because the liabilities are calculated based on token price and tokens in circulation. Token price on the other hand is shown in figure 76. We can see a stable increase with an average price after 5 years at 1.060, which is roughly 1.2% growth that we initially set. It is slightly lower (because 1.2% should be exponential over 5 years) because in the many different simulations that we have made, there are some when our CAR ratio falls low and we freeze the index growth for a while. We can also see the lower values of of price, indicating how low we could go in our simulation in figure 77. We can see that due to our issues in 1% of the worst cases our price can go as low as 84 cents. However, if looking only at 5% of the worst cases we can find that it is unlikely for us to drop more than 10% in value. A big part of this issue is due to quite high volatility of our designed index.

We invested quite a lot in deposit pools in this simulation, which we will discuss later on. But due to this investement we expect to have relatively stable network and collateral. The latter can be seen in figure 74. We can see that in the long run we on average slightly increase collateral (and on medain as well) to 1.0024 (and median to 1.0052). This shows that overall our network is financially viable in the long run. We also inspected the 1st, 5th and 10th percentile of worst cases there in figure 75. We can see that the collateral drops to as low as 75% in 1% of the worst cases, which low, but still sustainable. In 5% of the worst cases it only falls to 92% which is very manageable and supports the stability thesis of this system. So in terms of the simulated collateral with our strategy, we seem to be quite stable. Note, we might employ some additional defense mechanisms when some extreme cases have very low collateral or CAR ratios, such as resetting the index to a lower value, when we find the optimal conditions to employ such a mechanism. This is a subject of an ongoing research.

We looked at how our investments perform in figure 78. They perform similarly as liabilities and collateral, which seems to be quite stable. So, there are no interesting findings there. We also inspected performance of low, medium and high risk pools in figures 79, 80 and 81 respectively. The same as in one path simulation, we see quite a bit of rebalancing in the first year, which then eases after that once our strategies become clearer.

A very important part of our design are also deposit pools. Unfortunately we have not modeled them in perfectly stable way - they allow for big jumps in the number of depositors. We expect such jumps in real world too. This is because this is impacted quite highly by the market confidence and the confidence in our coin. This is usually quite a volatile metric, so jumps are expected. But we also tend to overinvest at the beginning in the deposit pool due to initial investment by foundation. This makes sense since the initial investment assures some very much needed initial stability in the system. This can be somewhat seen in figure 82. We can see that after one year when initial depositors redeem their appreciated deposits, we have some decrease of deposited tokens. However, this decrease is not too big, as we can see in figure 83. We lose around 5% of the depositors on average. Note, the amount of depositors is modeled in a very conservative way, so it is likely that on average we will have more than 10-15% of the depositors in our pool, which will have numerous positive effects for us. Still, even with such modeling we expect the long term amount of depositors to be between 5 and 30 % with an average around 15%. We also look at the lowest percentages of deposited tokens in worst randomly generated paths in figure 84. We can see that that drop after one year is even more prominent there. However, even the very negative long run, we are unlikely to have less than 4% of overall tokens deposited. This shows that we can rely on deposit pool in quite a big way and that it is likely that it will be relatively popular among the investors.

The next thing to look at when it comes to the deposit pool is how much we invested in it. Figure 85 shows just that. It somewhat follows the graph on deposited tokens over time. We can also see the deposit interest rate over time in figure 86. We can see that in lower bound we set the minimum set (our conservative assumption is that the depositors will always demand at least 3% return) and the upper bound seems to be quite volatile, but is at around 13%. In the long run the deposit rewards are thefore around an average of 6%.

We also plotted our capital adequacy ratio. It is a very important decision tool, guiding us with investment decisions such as negative what-if scenarios. So, if the CAR is low, we adjust our strategy in order to get it back up, so we can avoid the defaults. We discussed the defence mechanisms in section 5. In figure 87, we can see that average CAR values remain stable over time at around 95%. Note, there is some volatility at the first year because of the rebalancing of the assets to adjust for different risk taking. Even later on there is some volatility due to the discounting of deposits. When discussing CAR we wanted to take a look at what happens in most negative cases. They are shown in figure 88. We can see that in the 1% of the worst cases our CAR goes below 70% and can also sometimes force us to employ the defense mechanisms. For many simulations it did go below those values before, but our defense mechanisms help pushing the values back on. However, it is possible that if we have a very bad outcome, our CAR values decrease in the long run, pushing us to think of possible defense measures. But overall, CAR seems to be stable and helps with the stability of the system.

We also have an interesting situation regarding the foundation revenue. It is displayed in figure 89. We can see that in upper bounds we get a lot of revenue. This is in big part due to the circumstances that happen after coin runs. A better overview on revenue (at least from risk management standpoint) is available if we look at median and lower bound. This is displayed in figure 90. On median path, we get around 1 million of revenue after 3 years and is then increasing to a few millions ($4.1 million to be exact) after 5 years. First year we get around a quarter million and second year a bit over half a million. In lower bound, we consider our coin (relatively) unsuccessful and we get around

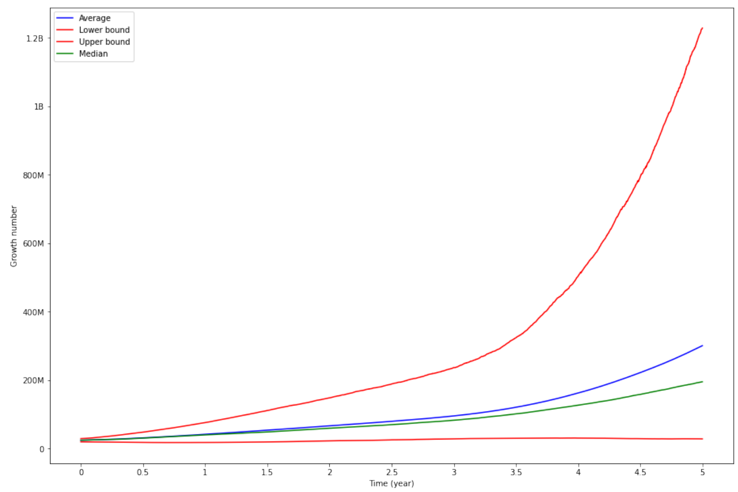

Figure 65: The simulated network growth over time (averages and upper/lower bounds)

11,000, 22,000, 28,000, 20,000 and 26,000 dollars revenue per years. This is not enough to sustain our operations, but this is only the case in the event of the very negative run. Note we will also offer more coins, so each coin can potentially bring us more than enough revenue in the long run.

Finally, we will also add some information that we cannot find on the graphs. We experienced the CAR ratio of below 0.5 at least once in our simulated path (what we consider a worrisome value) in 0.68% of all the paths. We gave money to the foundation at least once 3.45% of the times.

6.3 Simulation with 2% index yearly appreciation

Above, we have made a simulation using an assumed 1.2% average return of our underlying index. However, we might want to have an index that appreciates more than that. We might want to have an index that appreciates 2% per year on average (and still maintains the same volatility). In order to make such model sustainable, we have to make some different strategy. The strategy is described in section 5.5. Here we will show some key results. For brevity, we omit most of the figures. We did not plot a single path simulation because it is very similar than the one for lower risk investments. There is a bit less of the liquidity reserve and the amount of invested in deposit pool, but we will rather show those key results from our Monte Carlo simulation with 10,000 runs for the higher risk model as well.

Even in Monte Carlo simulation with higher risk strategy we omit some figures that are very similar than the ones in lower risk strategy. Some are expected to be exactly the same (such as the returns modeling) and some have only small differences. Those are the amounts invested and managed in investment pools,

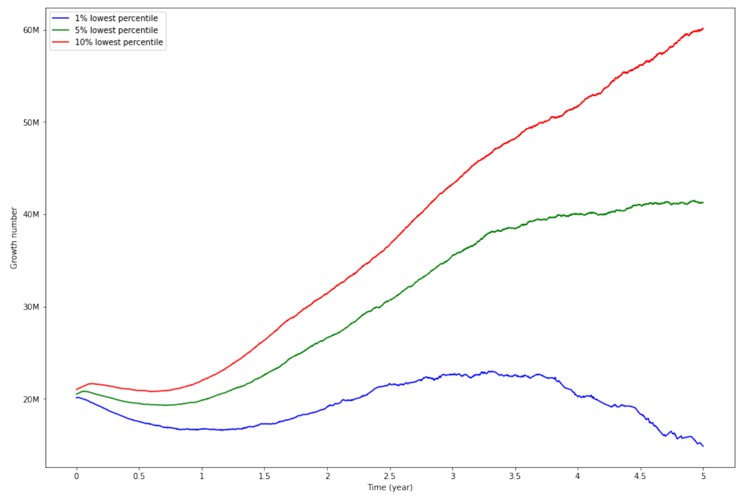

Figure 66: The simulated network growth over time (lowest 1st, 5th and 10th percentiles of simulation)

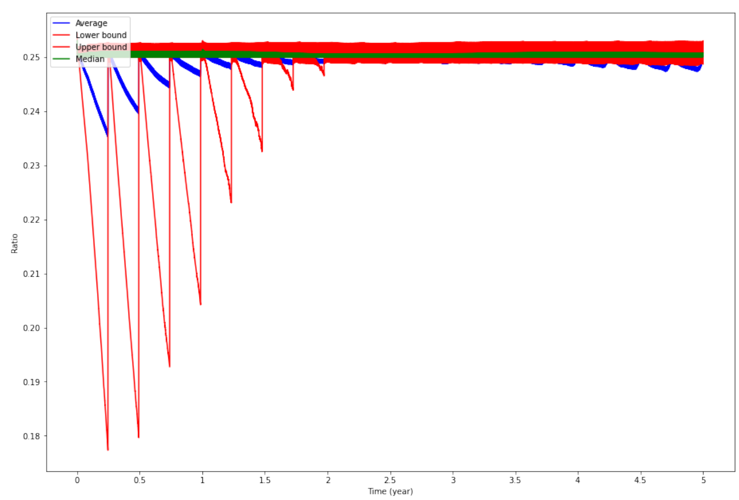

Figure 67: The simulated share of the liquidity reserve over time (averages and upper/lower bounds)

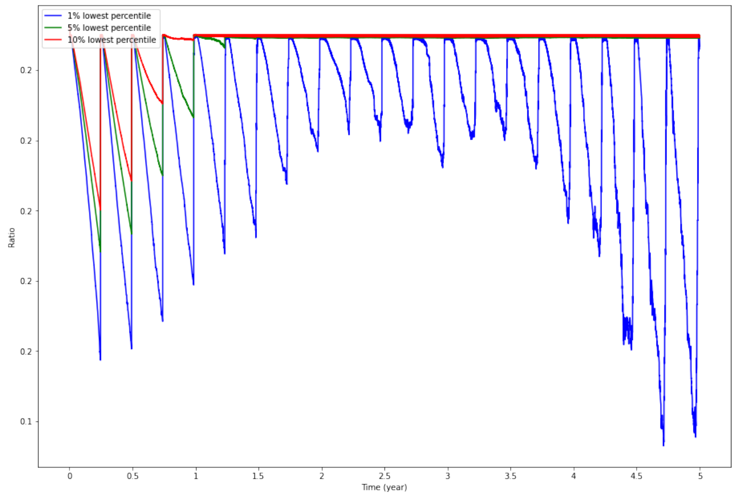

Figure 68: The simulated share of the liquidity reserve over time (lowest 1st, 5th and 10th percentiles of simulation)

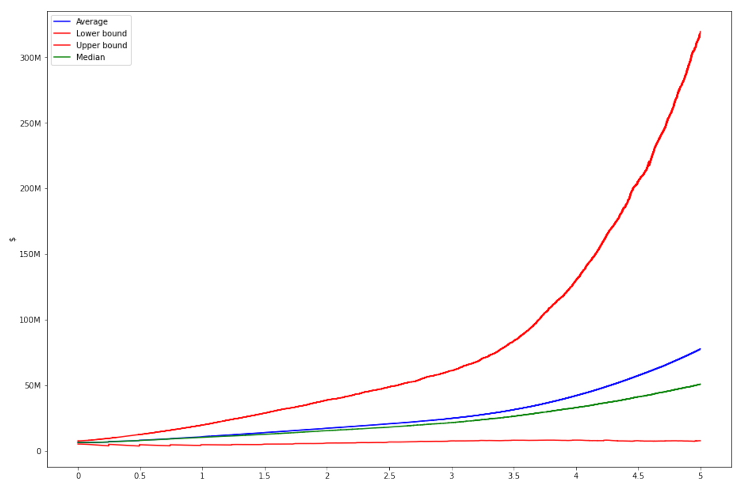

Figure 69: The simulated the liquidity reserve over time(averages and upper/lower bounds)

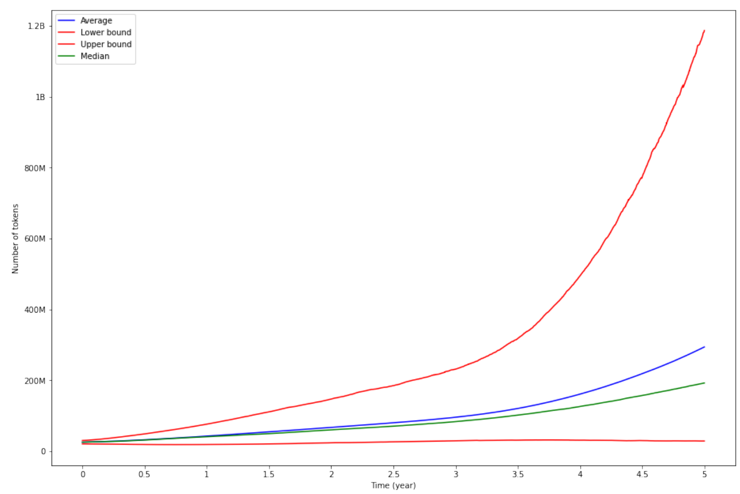

Figure 70: The simulated number of tokens in circulation (averages and upper/lower bounds)

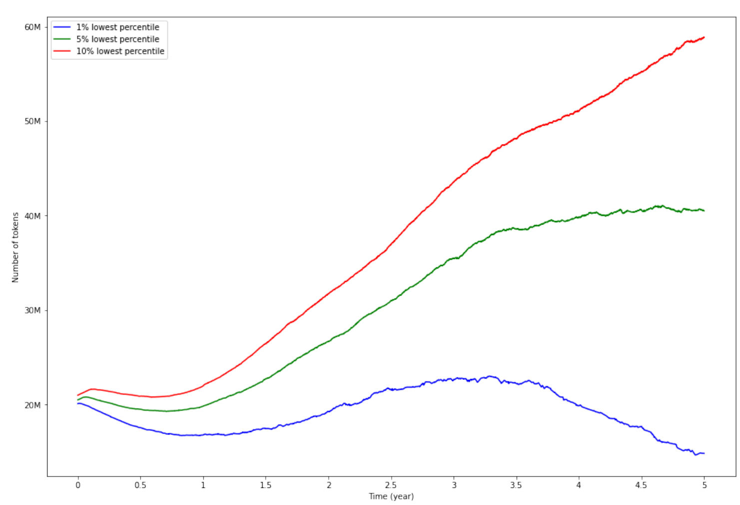

Figure 71: The simulated share of the liquidity reserve over time (lowest 1st, 5th and 10th percentiles of simulation)

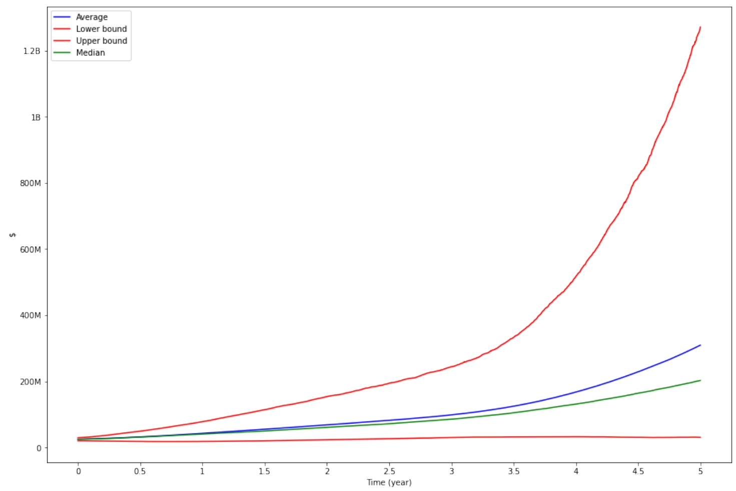

Figure 72: The simulated amount of liabilities (averages and upper/lower bounds)

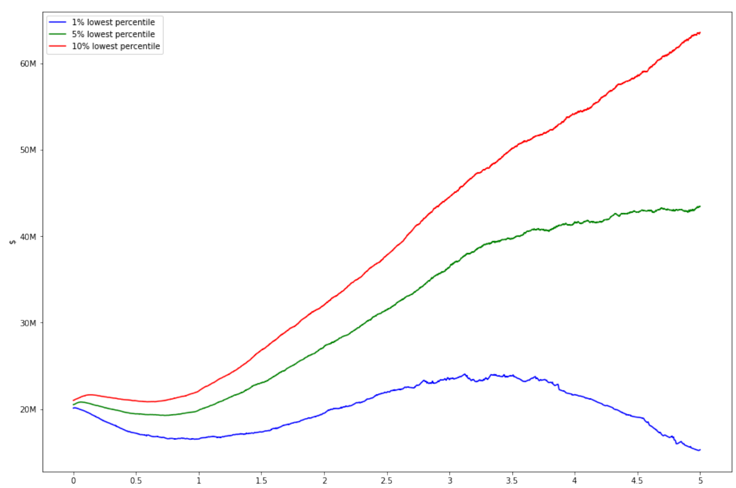

Figure 73: The simulated share of the total amount of liabilities over time (lowest 1st, 5th and 10th percentiles of simulation)

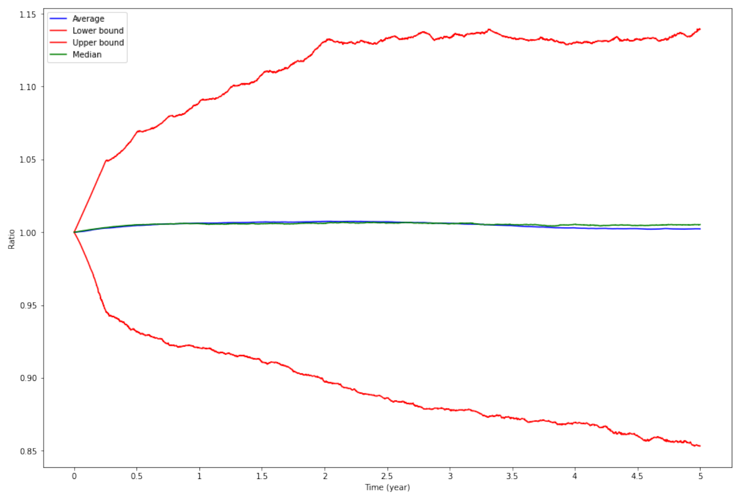

Figure 74: The simulated share of collateral over time (averages and upper/lower bounds)

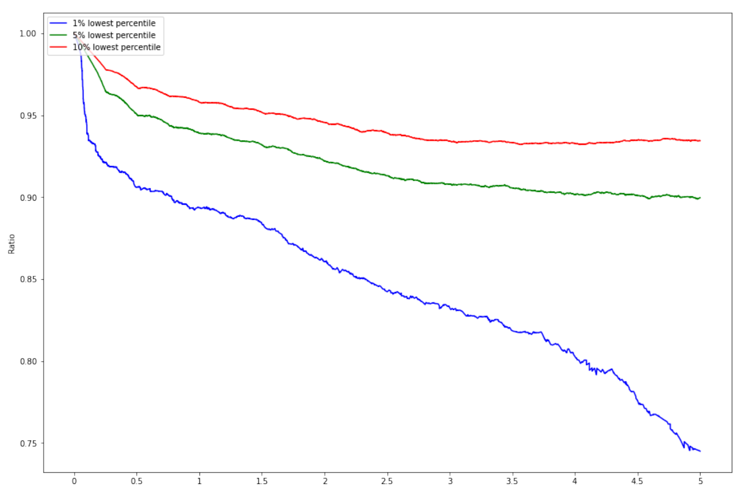

Figure 75: The simulated share of collateral over time (lowest 1st, 5th and 10th percentiles of simulation)

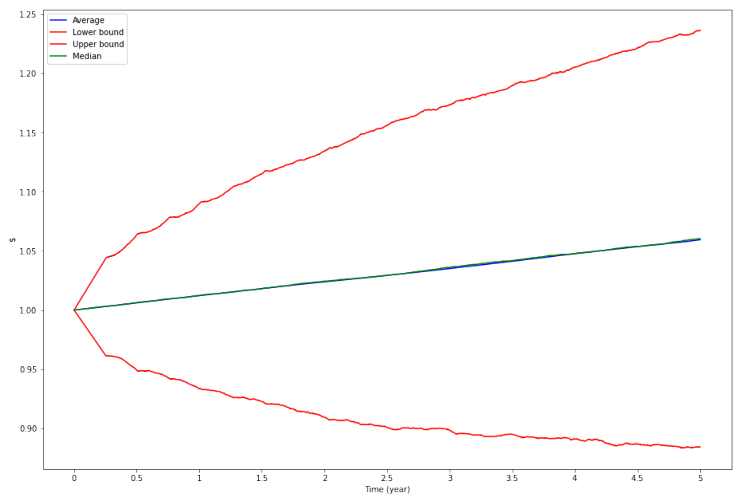

Figure 76: The simulated price development over time (averages and upper/lower bounds)

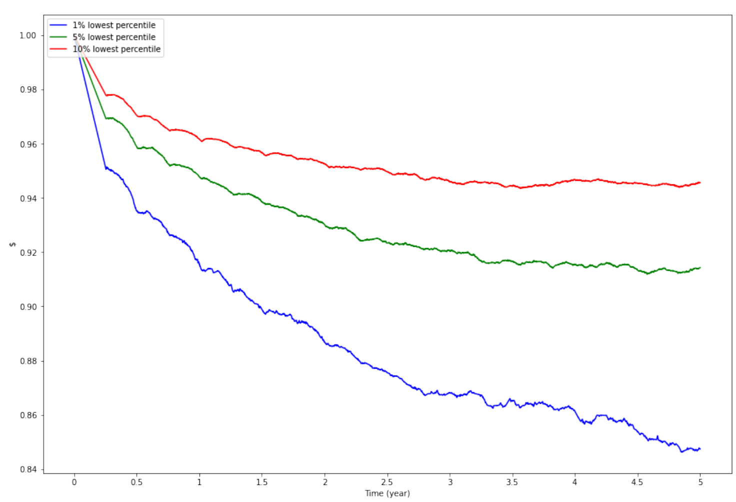

Figure 77: The simulated price development over time (lowest 1st, 5th and 10th percentiles of simulation)

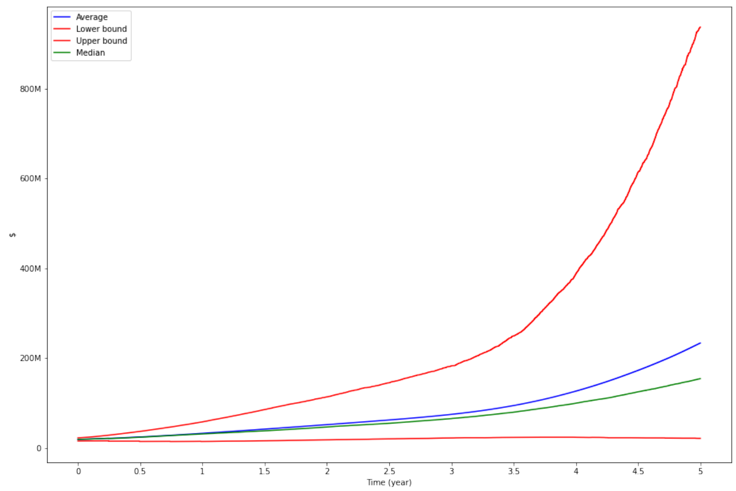

Figure 78: The simulated total investments over time (averages and upper/lower bounds)

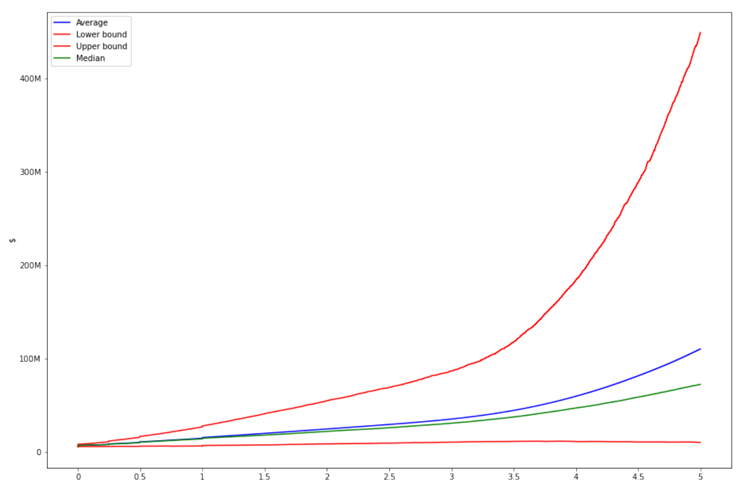

Figure 79: The simulated total amount invested in low risk investment over time (averages and upper/lower bounds)

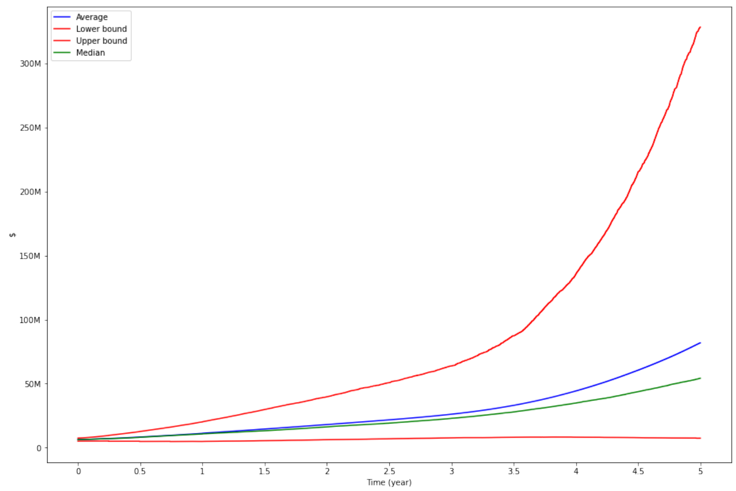

Figure 80: The simulated total amount invested in medium risk investment over time (averages and upper/lower bounds)

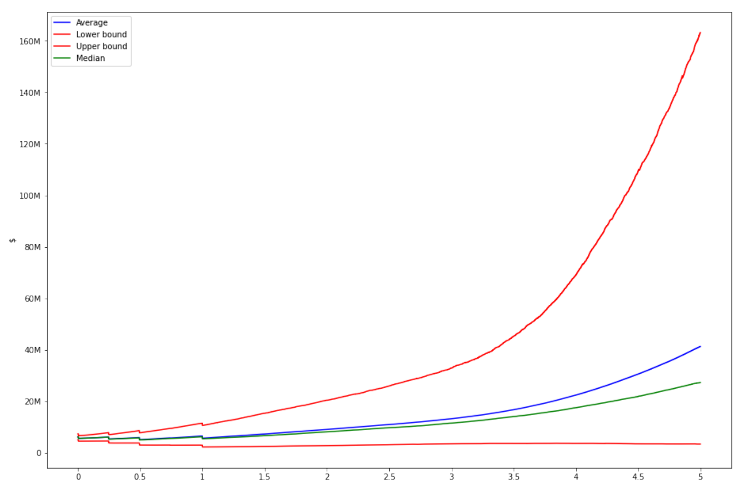

Figure 81: The simulated total amount invested in high risk investment over time (averages and upper/lower bounds)

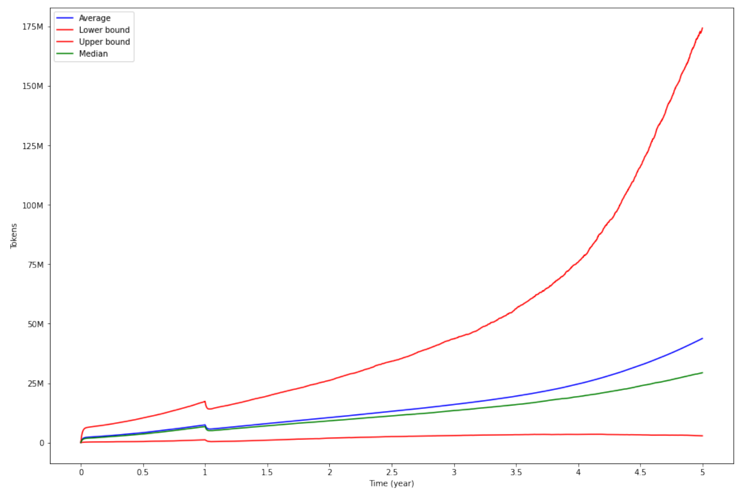

Figure 82: The simulated number of deposited tokens over time (averages and upper/lower bounds)

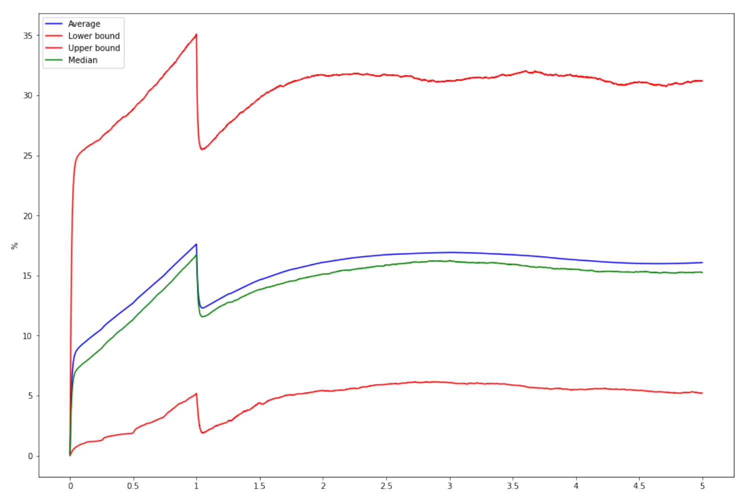

Figure 83: The simulated percentage of deposited tokens over time (averages and upper/lower bounds)

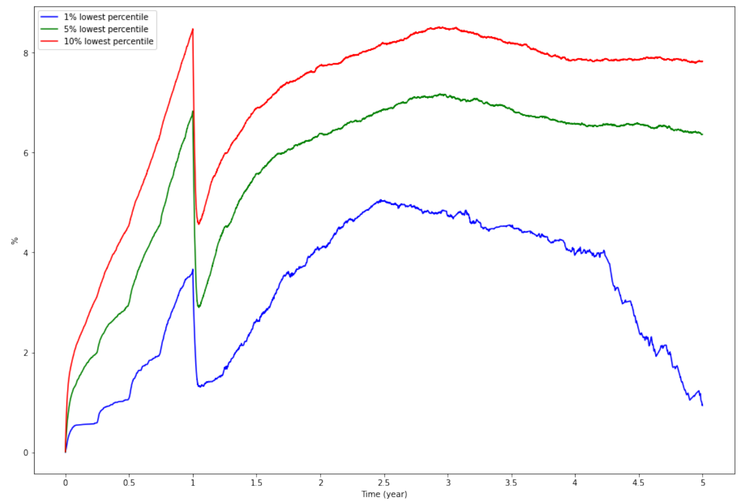

Figure 84: The simulated percentage of deposited tokens over time (lowest 1st, 5th and 10th percentiles of simulation)

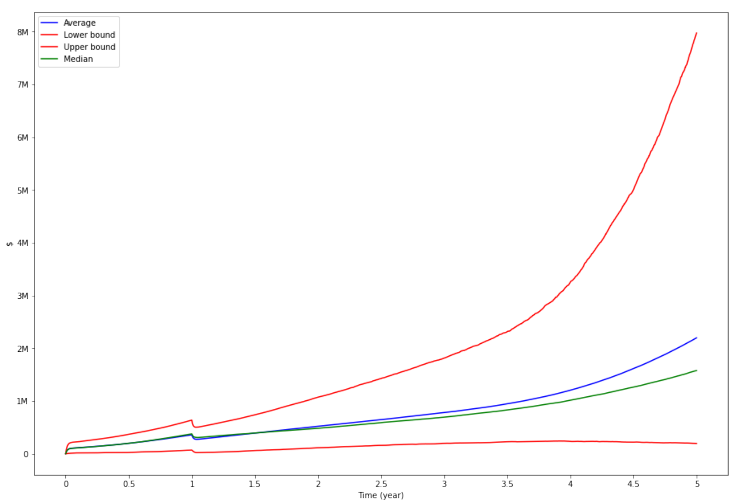

Figure 85: The simulated total amount of USD invested in deposit pools over time (averages and upper/lower bounds)

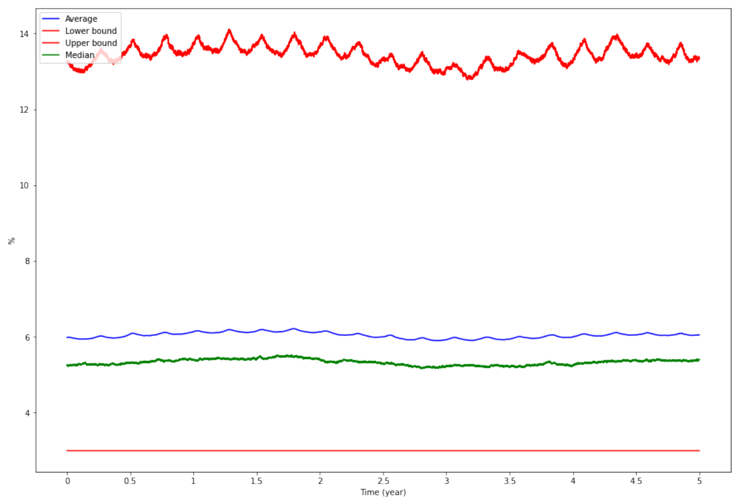

Figure 86: The simulated development of deposit rate over time (averages and upper/lower bounds)

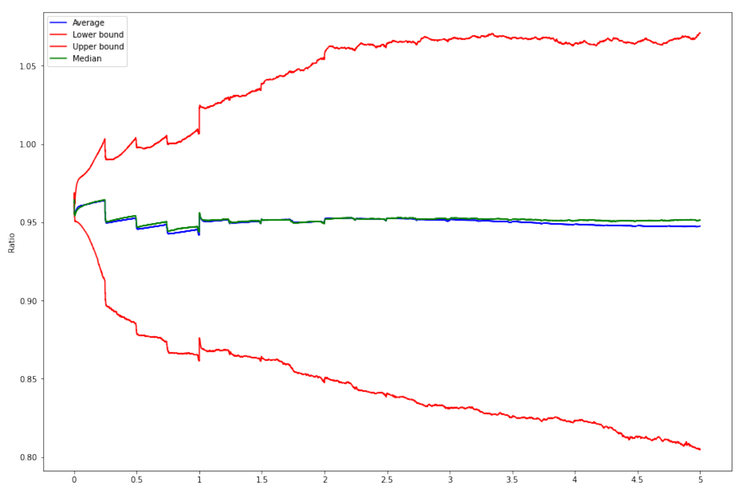

Figure 87: The simulated development of Capital Adequacy Ratio over time (averages and upper/lower bounds)

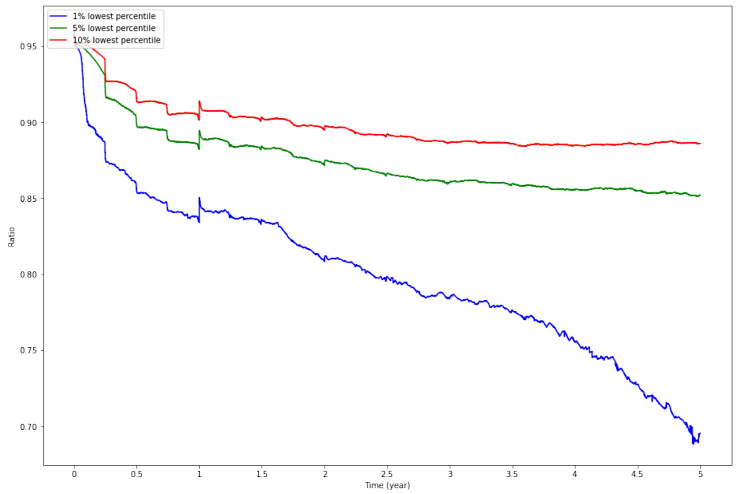

Figure 88: The simulated development of Capital Adequacy Ratio over time (lowest 1st, 5th and 10th percentiles of simulation)

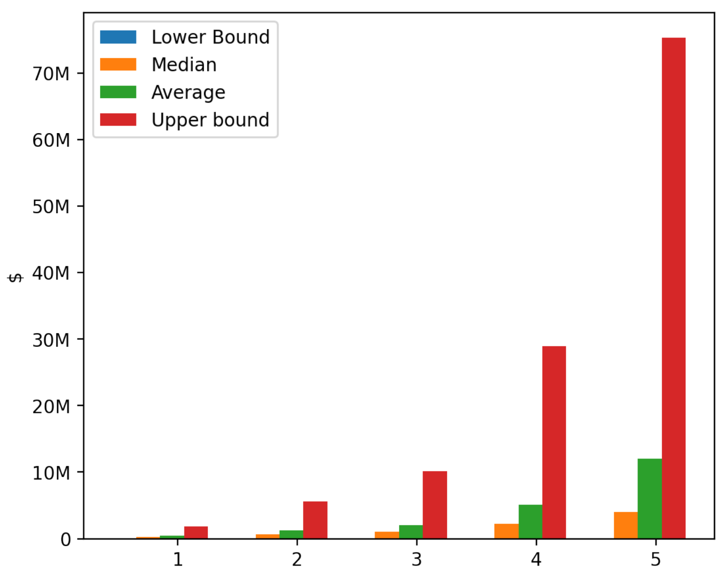

Figure 89: The simulated foundation revenue over the years

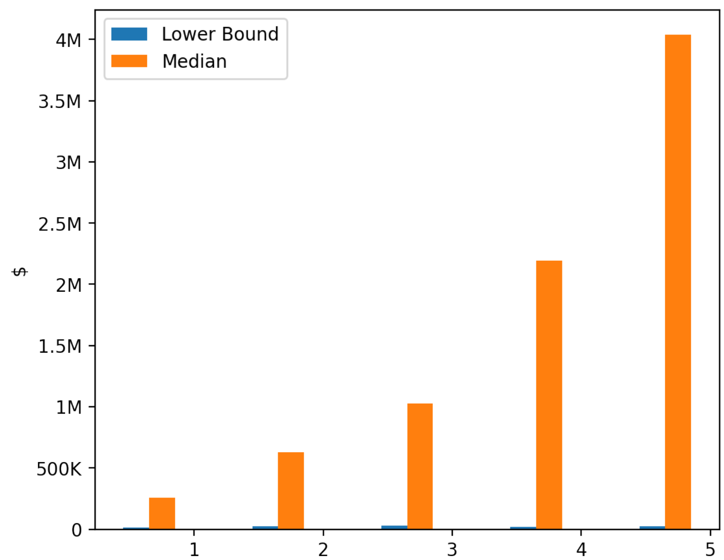

Figure 90: The simulated foundation revenue over the years (medium and lower bound)

liquidity pools and deposit pools as well as the number of tokens, growth and similar. While the numbers are different, the graphs look very similar and we will be more interested here in other parts of simulation where our new strategy might perform in a different way under pressure.

We can see the development of our fractional reserve in figures 93 and 94. Fractional reserve is behaving in a very similar way as it did for lower risk investment strategy. We have some jumps in the beginning where lower 2.5% bound falls to as little as 7% fractional reserve ratios at the worst times, but it then stabilizes over the time. We are still holding the liquid reserve under control most of the time. In 1% of the worst cases we do sometimes in very bad situations go below 2% fractional reserve, which is problematic and calls for action - but again - it only happens sometimes in 1% of the worst cases, likely because of very low CAR. So we might have to adjust index price in such a case, to evade this situation.

Another interesting thing to look at is the number of tokens in circulation. While the growth is very similar to the one in lower risk assets, we do have a bit more of the tokens in circulation under this strategy. We end up with a median of 204 milion tokens in circulation. In 2.5% of the worst cases for the outcomes in that category, we have around 21.6 million tokens in circulation (or less) at the end of our simulation. That is a bit higher than in lower risk investment strategy. The reason for an increase is that our growth model assumes that index returns play a role at the growth of the network and with this the influx of investors. Due to relative small importance of the index constant parameter, the growth was relatively mild for the 0.8% additional increase of index per year. Still, we can expect more investors here if the economics beind the model is successful. We can see the price appreciation in figure 95. Note that in the end of year 5 we get the average price of 1.099. This is very close (but slightly lower) to the expected 10% appreciation that is programmed in average index returns (given that it is exponential growth, we would expect slightly above 10% after 10 years). This is not surprising because in many of our simulations we hit less than 60% CAR where we freeze the returns. Another interesting observation can be seen in figure 96. We can see that in the worst 1% of the cases the average price for roughly 11%.

Another thing that we should always pay attention to is a level of collateral that we have. If we want a stable economic model, we should have the collateral of at least the average of 1 in the long run (5 years). Because this means that our model is designed to keep a good collateral ratio in normal circumstances. We can see in figure 97 that in high risk model the collateral ratio does end up above 1 after 5 years. Even if we look at the worst cases (figure 98), we can see that we still keep collateral at around 70% even in 1% of the worst cases. Here we have some problems due to the fact that low collateral sometimes triggers a coin run, so we might apply a reduction of price when CAR is low enough. However, when we trigger such a mechanism is still a subject to an ongoing research.

Our deposit pools are depressed quite a lot under this strategy. We invest considerably less and initial investment done by the foundation is therefore much higher compared to further investments. This is shown in figure 99. After one year we have a significant drop of deposited tokens. This is because the initial investment from foundation is still the same as in case of lower risk investments, but all further expenses we did are considerably smaller. Smaller deposit pool is an unwanted, but necessary consequence of this strategy.

We also plot the development of capital adequacy ratio in figure 91. In this simulation we also have a volatile start in first year due to rebalancing and then slowly stabilize around a value just below 95%. In the worst cases (plotted in figure 92), we do see a bit of a problem because in the lowest 1 % of the cases in that category we do have a CAR ratio below 65% after 5 years. This means that we have to freeze depostor's returns in around 1% of the worst simulations. While this is not ideal, it is still not a very high chance that we would have to do this in real world. So, the system does enjoy a relative stability. Finally, we also recorded 0.95% of the cases when CAR dropped below 50%. While we are not taking actions at that percentage, we do monitor it as a potential low and concerning value of CAR.

We are also interested in foundation's revenue. They are plotted in figure 89. We can see that in the highest 2.5% of the cases we can hit the foundation's revenue of up to $100 million in year 5. This is in big part due to bank runs and the low collateral that we keep after our protocol starts raising again after them. It is questionable if the users would invest that much with high slippage, so perhaps a better metric to look at is the median revenue, which is better shown in figure 90. Note, while it is not likely that new investors would pay a

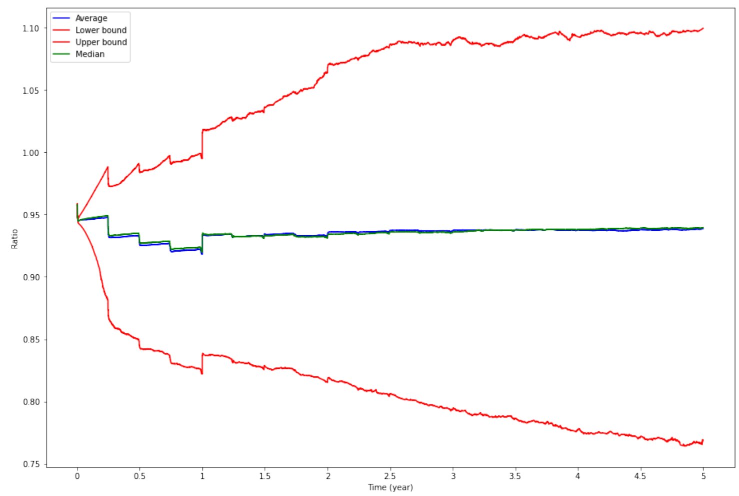

Figure 91: The simulated development of Capital Adequacy Ratio over time for higher risk strategy (averages and upper/lower bounds)

significant slippage after a coin run, that does not mean that they would not invest and add to the growth of the model. They would most likely just wait until the slippage amount drops, which happens relatively fast, as it will be discussed later on. At median revenues, we still start gaining over $1 million in year 2 and onwards, making our coin quite profitable for foundation as well after a while. In the lowest 2.5 percentile, the foundation gets around $13,000, $22,000, $35,000, $30,000 and $31,000 per year in year 1,2,3,4 and 5 after the launch respectively. We can see that we have some revenue even in the worst cases and a relatively high revenue in median case.

Finally, we discuss the fractional reserve in more detail. We hit less than 5% of the fractional reserve in around 17.5% of the cases. When we do hit this, we stay at below 5% for a median time of 371 hours (15 days). In this statistic, if we hit below 5% more than once in one simulation, and we had more than one duration when we stayed below it, we look at the longest time we stayed under 5% of fractional reserve. Furthermore, we dropped below 2% of the fractional reserve in over 15% of the cases and stayed there for a median of 153 hours or a bit over 6 days. This is when we also let the temporary loss of peg to the index. This means that it can happen that we lose a peg for some extended (expected less than a week) period of time. Another interesting statistic is that we gave the money to the foundation due to good CAR in 6.37% of the cases.

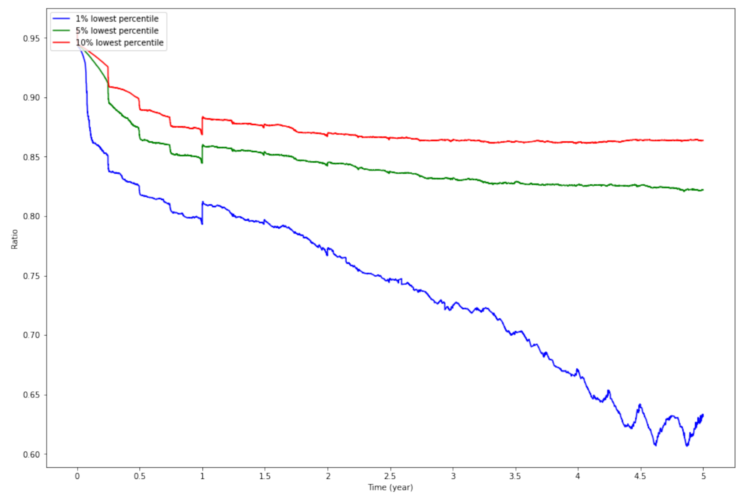

Figure 92: The simulated development of Capital Adequacy Ratio over time for higher risk strategy (lowest 1st, 5th and 10th percentiles of simulation)

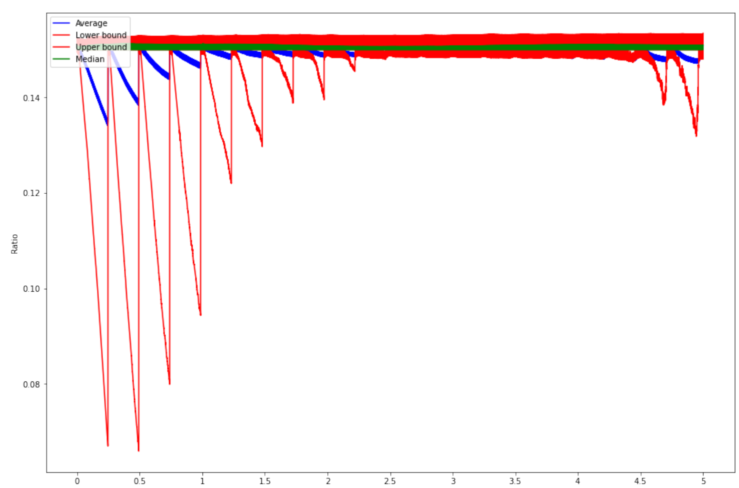

Figure 93: The simulated share of the liquidity reserve over time for higher risk strategy (averages and upper/lower bounds)

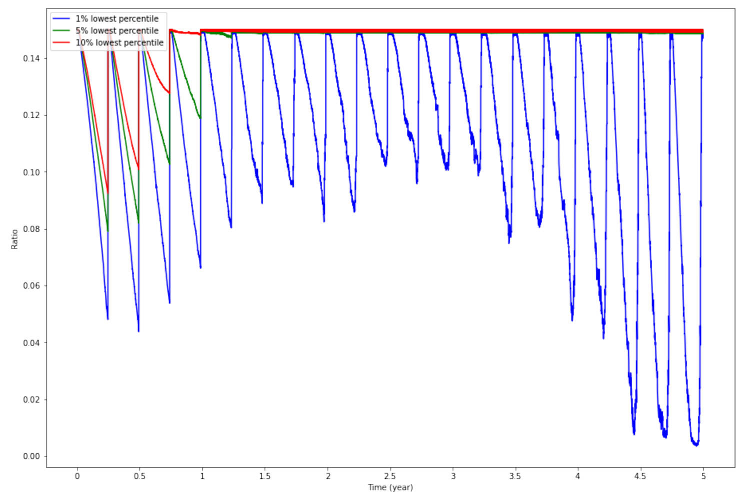

Figure 94: The simulated share of the liquidity reserve over time for higher risk strategy (lowest 1st, 5th and 10th percentiles of simulation)

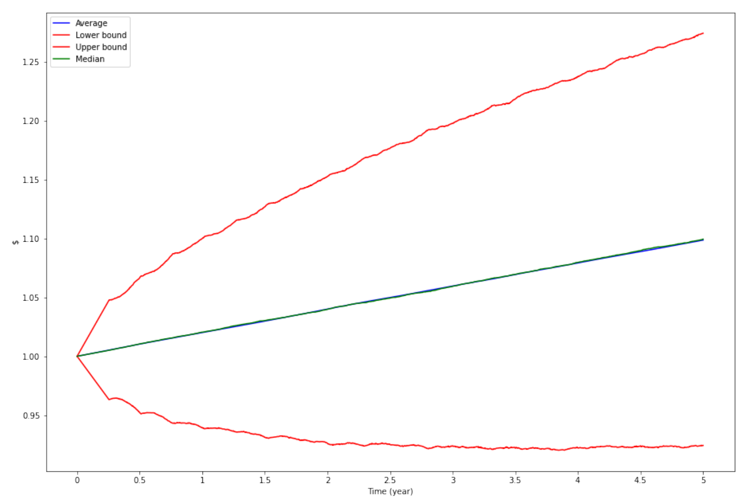

Figure 95: The simulated price development over time for higher risk strategy (averages and upper/lower bounds)

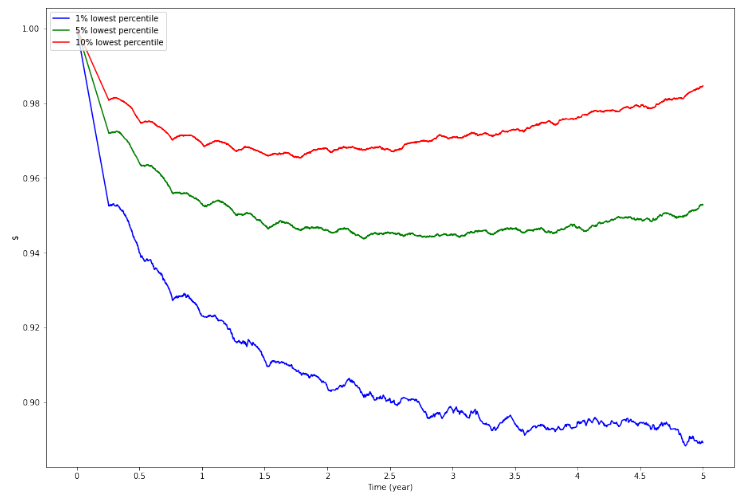

Figure 96: The simulated price development over time for higher risk strategy (lowest 1st, 5th and 10th percentiles of simulation)

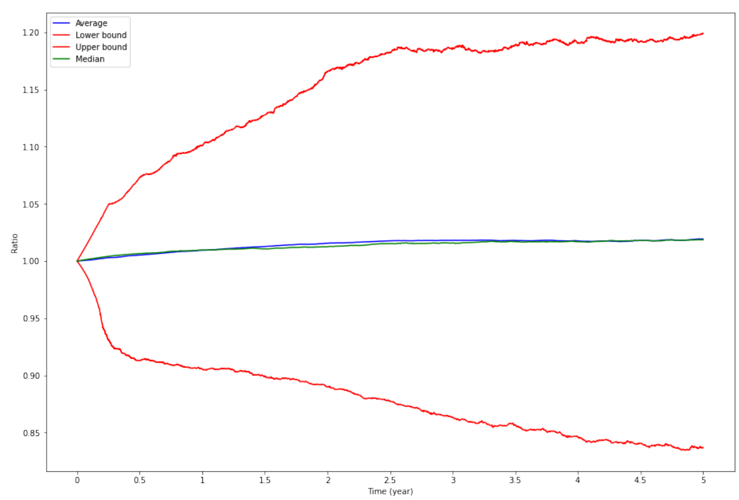

Figure 97: The simulated share of collateral over time for higher risk strategy (averages and upper/lower bounds)

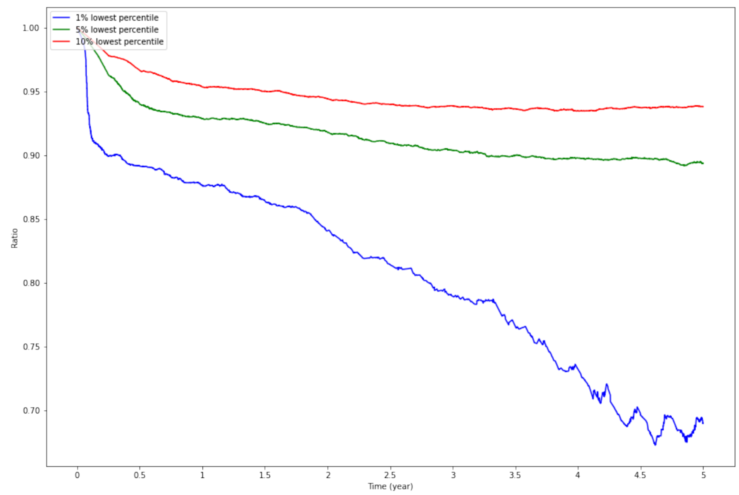

Figure 98: The simulated share of collateral over time for higher risk strategy (lowest 1st, 5th and 10th percentiles of simulation)

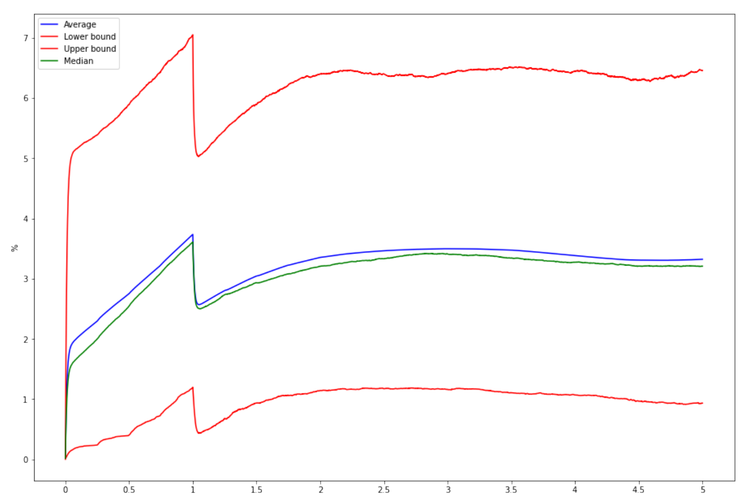

Figure 99: The simulated percentage of deposited tokens over time for higher risk strategy for higher risk strategy (averages and upper/lower bounds)

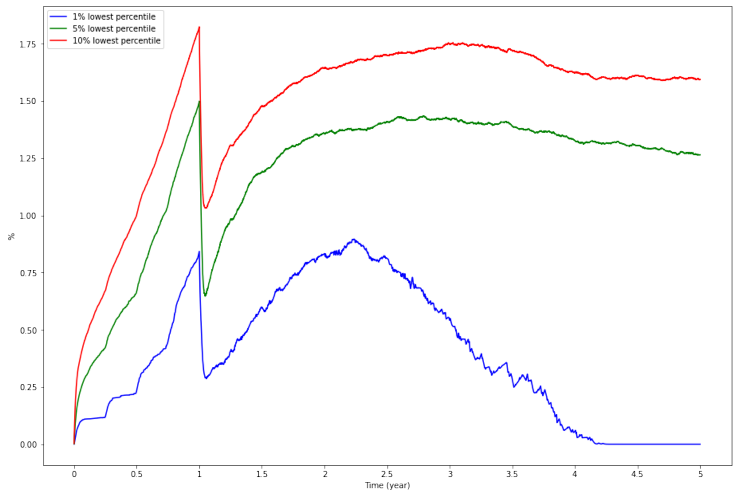

Figure 100: The simulated percentage of deposited tokens over time for higher risk strategy for higher risk strategy (lowest 1st, 5th and 10th percentiles of simulation)

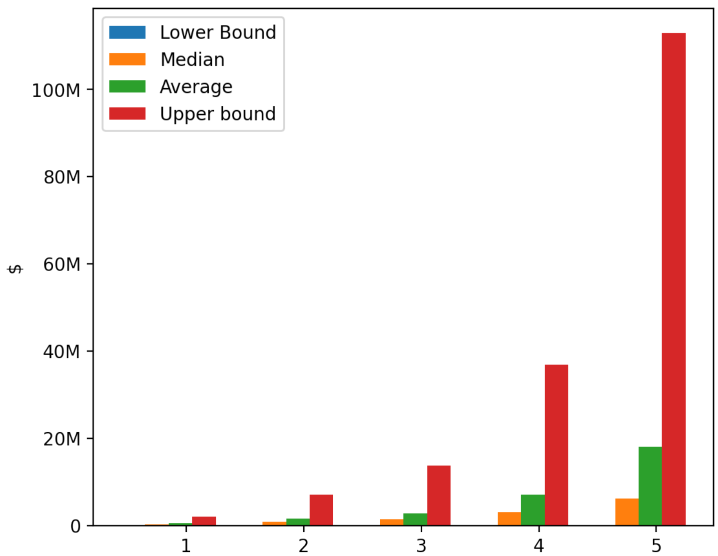

Figure 101: The simulated foundation revenue over the years for higher risk strategy

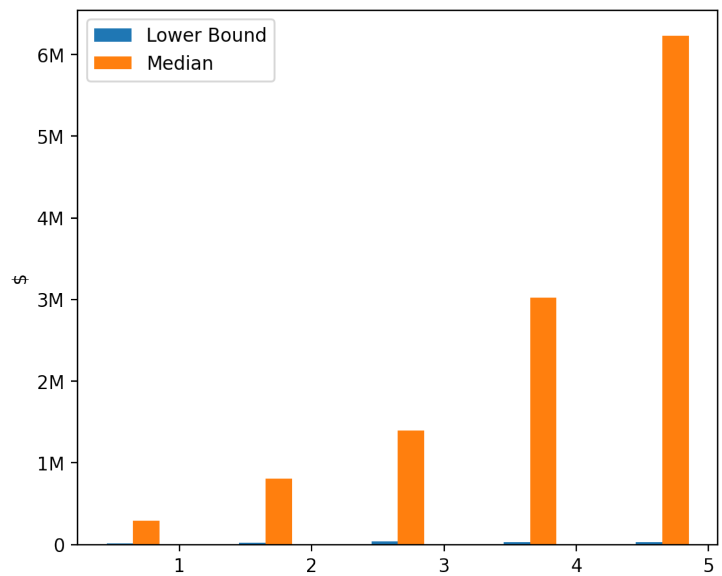

Figure 102: The simulated foundation revenue over the years for higher risk strategy (medium and lower bound)

7 Conclusions

In this paper, we attempted to simulate and estimate the stability of the proposed Cogito protocol. We simulated the protocol to move by mathematically implementing proposed features, such as fractional reserve, investment pool, deposit pool and others. We simulated our investments in relatively safe assets - staking pools. Even though staking pools are considered relatively safe, they are not without risks, so we did estimate and simulate the possibility of their default and our potential losses of funds. As such our simulation is relatively complex. We assumed the returns and probabilities of default to be as close to what is actually happening on the market as possible. We also estimated what will be the general interest of our coin based on the variety of factors with which we were able to (to some extent) reproduce the successes of several stablecoins. We then decided to be cautious and penalize the general interest in order to err on the side of caution and at the same time prepare in case there would be a reduced demand for stablecoins in the future. Furthermore, we do not assume to have any hype and hype parameter is modeled as a random process with zero drift. With this we assume that it will not enjoy any special hype compared to other coins. As such our model is relatively conservative when it comes to forecasting future performance of our coin, but this helped us to better focus on risk management. So the results should not be interpreted as the returns and stability that we expect, but more of an analysis of a relatively pessimistic scenario and observing our performance in such a scenario, making sure that we are stable even in suboptimal conditions. We also added the probability of coin run, such as the one that happened in May 10th on the UST coin, which caused the general run on all the stable crypto coins. While we are not a stablecoin, we believe that such a run can also affect the low volatility coins where we belong. We also allow users to benefit from an increasing price of our index, which is another incentive for them to invest in us. Our simulation lasted 5 years in the future and involved a Monte Carlo run of 10,000 different paths.

We also created a strategy for our funds management with investments, fractional reserve and deposit pool. Our strategy makes decisions on what we do in different situation, such as if our collateral is low or if we have any other issues or if we go through special events. We applied this strategy on our simulation.

Our results show, that despite taking some cautious assumptions, our proposed design is stable. We rarely lose a significant portion of fractional reserve, except when it comes to coin runs, but even in such cases this is a relatively short occurrence that usually only lasts several days. We consider the the problematic cases when our internally defined CAR ratio falls below 50%. That happens in 0.68% of all of our cases in our large scale simulation. The potential upside, such that would add some assets to our foundation happens much more often, in 3.45% of the cases. But this is not the only (or the main) way for the foundation to gain revenue. We also gain it by slippage when trading on DEXes when there is a excess demand for our coin. In such a case we calculate that the foundation also gets an increasing revenue over time, starting from \$255,000 in the first year to \$ 4.040 million in the fifth year according to the median run of simulation. We show that in most of the cases we do not only make the economics of the coins that we propose stable in the long term, but we also make a significant revenue for the foundation from them. We further show that our protocol is stable even though it promises 1.2% average return per year with quite high volatility that is linked to the index.

Furthermore, our simulations show that at a return that we are offering, we can expect to have roughly 190-200 million of tokens in circulation by the fifth year. Those results likely underestimate the actual growth of the market, since we took some conservative assumptions on growth. Our collateral would on average (and median) end up slightly above 1 and CAR (the metric that we use to determine our strategy) at around 95%. We estimate that between 5 and 30% of our tokens will be deposited in long term deposits, offering returns of around 5-6% on average.

We further invest a big portion of our funds into the deposit pool. There the users can take deposits and gain interest on them after a year of time. While taking some conservative assumptions there, we show that the users can deposit a significant portion of their assets there, gaining very good additional appreciation (besides the natural appreciation of the token, which follows the index) and keep the relatively low risk that our protocol enables. They also help with the stability of the protocol since they soften the potential coin runs and sudden outflows of capital. While the amount of tokens in the deposit pool might vary quite a lot depending on the market conditions, we do keep a substantial amount of holders for most of the time even if the market conditions are not the best. We rebalance quite often and there are some shocks of the amount of deposited tokens because of rebalancing, however they do not have major negative consequences on overall financial health of our protocol.

As such we show that our protocol is financially stable and can attract many different types of investors. One type are the investors who would just like to use it for a while between trading other coins. The other type are the longer term investors who want to gain a safe return over a period of type by either depositing the token or just holding it for a longer period of time. This gives us the ability to promote our protocol in many different ways.

Besides that, we made another simulation where we assumed an average of 2% index growth and with that our price appreciation. We employ another, riskier strategy and we show that even in this strategy we can expect a stable growth, good collateral and CAR ratios in most cases and relatively low risk of dropping our internal CAR ratio below 50%. This happens there in around 1% of the cases, however in much more cases we reach a very good ratio, where we give some assets to our foundation (in 6.37% of the cases). The foundation also gets considerably more money (around $ 6.2 million in year 5 according to the median outcome) and we have (in median outcome) around 204 millions of tokens in circulation at year 5. Our deposit pool is smaller in that strategy, however we still have some depositors there. So we show that we can also manage to reach a 2% index appreciation with a relatively low risk.

The main outcome from our simulation is that even though we do assume that overall cryptocurrency market shocks are common and big, we do have a strategy that is managing to work around them and stabilize our own protocol, which can then offer several investment products. It enables us to track different indexes without much risk. Since the risk of a negative outcome in our protocol is reasonably small (the risk of default, that is decrease of index or just a freeze on the index itself as one of our defense mechanisms), we can then offer small returns with a small amount of risk. While this does not classify our product as a stablecoin, it does show that we do have a low risk token.

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