A Paradigm Shift in Investing

A Model and Strategy Framework

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1. Executive Summary

This paper introduces a novel approach to investing: AlphaSquared, a classification and reactionary approach that focuses on reacting to current market conditions rather than attempting to predict future trends. This paper will delve into the intricacies of AlphaSquared, providing a comprehensive overview of its components, the challenges it addresses, and the rigorous testing framework that ensures its robustness. We will also discuss our vision for the future of AlphaSquared and how it can revolutionize the way retail investors interact with financial markets.

AlphaSquared is built around two central components: the Model Framework and the Strategy Framework. The Model Framework leverages a combination of traditional statistical models, asset growth models, technical analysis techniques, and custom algorithms to classify current market conditions into one single risk metric. This serves as the input to our Strategy Framework, which is designed to be adaptive to individual investors' needs and risk tolerance. We introduce a Dynamic Dollar Cost Averaging (DDCA) approach, which adjusts the size of recurring investments based on the risk calculated by the model.

To ensure the robustness of our approach, we have developed a rigorous testing framework, called Proof of Profit (PoP). This includes dataset sourcing and comparison, backtesting, simulations, stress testing, and forward testing. Traditional backtesting results indicate that our framework confidently outperforms popular benchmark strategies with confidence. More importantly our forward-testing results based on realistic price simulations, show that the Dynamic DCA strategy, informed by our risk model, results in significant profitability and asset accumulation during a variety of possible market scenarios. We go over three different simulated scenarios; *A)* a bullish future market spurred on by mass BTC adoption, *B)* a bearish economic recession with stagnant price action, and *C)* an in-between market characterized by little volatility. The scenario analysis reveals the impressive efficiency and robustness of our framework.

In conclusion, AlphaSquared offers a novel and innovative approach to investing that acknowledges the realities of the market and empowers retail investors to make informed decisions based on objective data, rather than succumbing to the emotional pitfalls of modern investing.

2. Introduction

Drawing a parallel to the California Gold Rush of the 19th century, today's financial markets have become a hotbed for entities providing tools and services to those aiming to generate profits as traders. These market players often tout their ability to forecast market fluctuations, promising lucrative returns to investors. Despite a plethora of evidence debunking their predictive prowess, the demand for their services remains robust. Why? Clearly, if these market players can convince investors that forecasting market trends is a prerequisite for financial gains, it cultivates a significant demand for their predictive capabilities. Despite their consistent inability to accurately anticipate market shifts, they persist in advocating this belief. But what if this assumption is not only unattainable but fundamentally flawed? Having personally navigated these hurdles, we understand the struggles of the modern investor. That's why our Vision is more than just a business goal—it's personal. We aim to empower investors with the tools and knowledge necessary to avoid such pitfalls.

Our solution to these challenges is embodied in AlphaSquared. We empower retail investors by addressing traditional disadvantages of retail investors such as limited time, data access, and knowledge processing. By leveraging custom built quantitative models that aims to classify rather than predict, combined with our DDCA approach, investors can overcome these challenges and emerge prosperous. Distinct from competitors, AlphaSquared doesn't overwhelm users with excessive data. We select and compute critical metrics, streamline decision-making, and deliver the information in a highly digestible format.

In the following sections, we will delve deeper into the intricacies of AlphaSquared. We will explain how our model works by providing a comprehensive overview of its components, and detail the rigorous testing framework that ensures its robustness. We will also discuss our vision for the future of AlphaSquared and how it can revolutionize the way retail investors interact with financial markets.

3. Background & Problem Statement

Many times, we have found ourselves at odds with the financial markets. Whether it'd be bitcoin in the bullrun of 2021, or the Marijuana boom in the Canadian stock market in 2016, we found that traditional investing and trading methods relying on predictions, always fall short in the long run.

The fundamental issue at hand is the inherent unpredictability of the market and the inability of retail investors to predict market trends consistently and profitably. Traditional investment strategies often rely on prediction models that are ill-suited to the realities of the retail investment landscape. These models fail to account for the vast disparities in resources and information access between retail investors and larger institutional players. This problem calls for a new approach to investing - one that moves away from attempting to predict the market and instead focuses on classifying and reacting to current market conditions. This approach acknowledges the realities of the market and can therefore lay the foundation for a framework that is both profitable and stands the test of time.

By leveraging a classification and reactionary approach, we enable investors to react optimally to what is happening in the market at any given moment. This approach is grounded in research and historical precedents. For instance, the Efficient Market Hypothesis, a well-established theory in financial economics, posits that it is impossible to consistently achieve returns in the market in a risk-adjusted manner, as market prices reflect all available information. This theory aligns with our belief that a reactionary approach, rather than a predictive one, is more effective for retail investors. The problem of market predictability necessitates a shift in investment strategies. AlphaSquared offers a solution that embraces this shift.

4. The Proposed Framework

Our framework is constructed around two central components: the Model Framework and the Strategy Framework.

In the Model Framework, we center our analysis on objective data harvested from a diverse range of sources to ensure a broad, balanced perspective. We then process this information using state-of-the-art statistical models and algorithms. The analysis generated from these models is tied to real-time price action, facilitating instant feedback to market fluctuations.

The Strategy Framework is designed to be adaptive to the needs and risk tolerance of individual investors while maintaining coherence with the insights generated by the Model Framework. One of the primary components of this Strategy Framework is the Dynamic Dollar Cost Averaging (DCA) method, which we'll explain in detail later. We'll compare it with traditional investment approaches, namely 'DCA' and 'Buy and HODL'' strategies, referencing recent research to illustrate its benefits.

Together, these frameworks provide investors with an innovative, dynamic, and data-driven way to interact with financial markets, demonstrating that beating the market is a possibility when armed with the right tools and strategies. This forms the core of our approach.

As we delve into the following subsections, we will take a closer look at each of these frameworks, their individual components, and how they work together to revolutionize investment strategies for retail investors.

4.1. The Model

Classification-focused modeling requires a fresh approach to data analysis - especially in the context of emerging assets. Our goal is to develop exceptional and robust models that excel in precise and accurate classification while navigating the turbulent waters of cryptocurrency. To eliminate as many assumptions and biases as possible, we exclusively incorporate raw, unfiltered, and objective data. By leveraging computational power, we can incorporate an extensive range of attributes and data points that would be overwhelming for human analysis. This enables us to consider a wide array of market factors, with the heavy lifting performed by computation. Our model employs a combination of models to achieve its elegant functionality.

4.1.1. Asset Growth Models

In addition to traditional statistical models, our classification model also integrates asset growth models. These models are designed to capture the growth patterns and trends specific to the assets under consideration. By incorporating these growth models into our framework, we enhance the accuracy and effectiveness of our classification outcomes. The fusion of statistical models and asset growth models enables us to gain deeper insights into the behavior of crypto assets.

4.1.2. Traditional Technical Analysis

To further bolster the classification capabilities of our model, we incorporate traditional technical analysis techniques. This approach involves analyzing historical price and volume data, identifying statistical patterns, and utilizing technical indicators (Dongrey, 2022). By integrating these time-tested techniques into our model, we enhance its ability to classify assets accurately based on their historical trends and market dynamics.

4.1.3. Custom Algorithms

In addition to traditional statistical models and technical analysis, our classification model harnesses the power of custom algorithms. These algorithms are tailored specifically to the challenges and intricacies of the cryptocurrency market. By leveraging innovative algorithms, we can capture complex relationships and dependencies among various market variables, enabling our model to make more sophisticated and nuanced classifications. The integration of these custom algorithms enhances the overall performance and adaptability of our model.

4.1.4. Maintenance and Future Development

Developing the model is only half the battle; ensuring its longevity and effectiveness requires ongoing updates. Recognizing the limitations of human-input data, which may be subject to biases and manipulation, we have implemented a self-learning mechanism within the model.

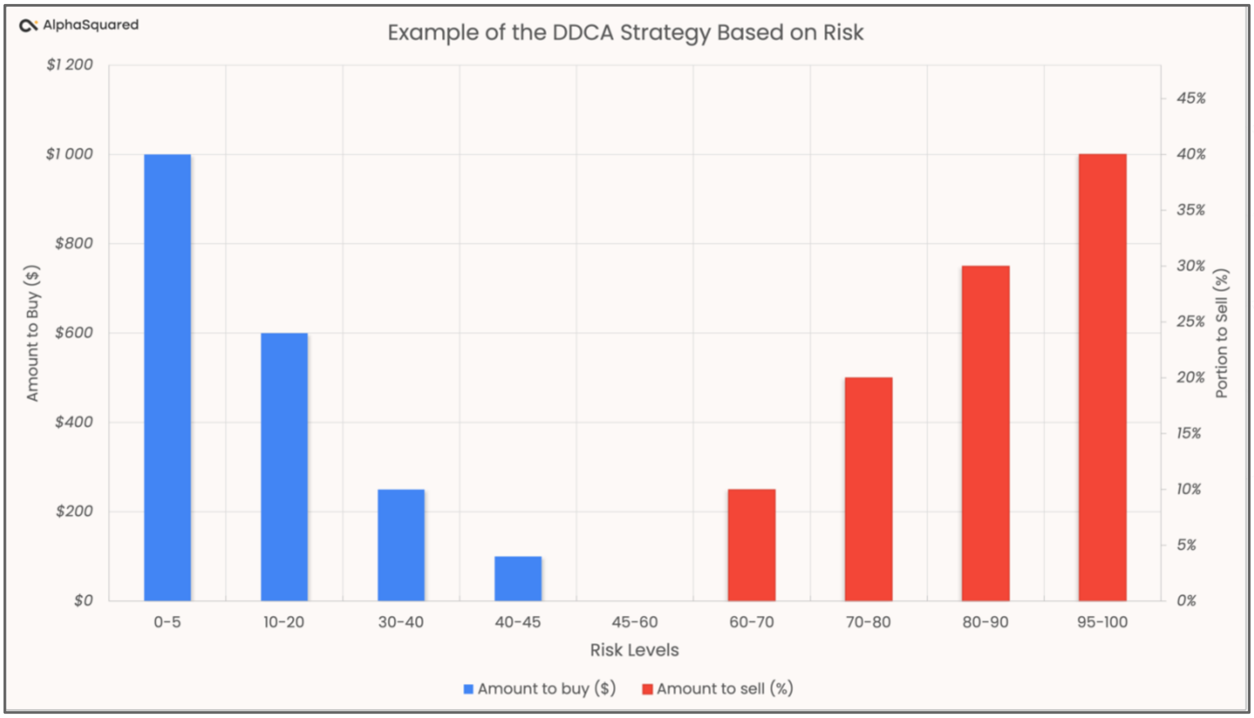
This automated process continuously gathers new data, analyzes it, and adjusts the model's parameters accordingly. This approach guarantees that the model's accuracy is maintained and, in all likelihood, improves over time. It is important to note that these updates do not retroactively alter past data points. Therefore, when evaluating the historical performance of the model, it will always reflect the value at the respective point in time.

4.1.5. User Interface and Risk Assessment

Despite the complexity of the underlying technology, we strive to deliver a user-friendly interface that simplifies the output of our classification models. Traditional risk-management tools often suffer from complicated user interfaces, primarily due to the involvement of the same individuals who design and use the system, as well as a “the more, the better” approach. Our ambition is to distill the model's output into a straightforward interface that preserves its complexity. The result is a risk assessment value ranging from 0 to 100, where 100 signifies the maximum level of risk associated with the asset, and 0 represents the least amount of risk. This user-friendly interface enables users to interpret and act upon the model's classifications with ease, making it as simple as riding a bike to utilize our powerful classification tool.

4.2. Strategies

With the model in place, it is crucial to design an effective strategy compatible with the workings of the model. Dollar cost averaging (DCA) is a familiar concept where an asset is purchased regularly over time, such as on a weekly basis, to mitigate volatility and risk (CFI, 2020). However, a trade-off exists as it also reduces potential profits. To deal with these shortcomings, we propose a dynamic approach called Dynamic Dollar Cost Averaging, which involves adjusting the recurring investment size based on some external factor. In this case, it is the risk calculated by the model. This means that as the risk decreases, you increase the dollar amount you buy for, and as the risk rises, you increase the amount of the asset you sell for. Naturally, a risk of 50/100 can be seen as a cutoff point where you do neither. This is where strategies play a crucial role.



Not everyone shares the same risk tolerance in their financial lives. A person in their early twenties might be more inclined to accept a higher risk-reward ratio compared to someone on the verge of retirement. Depending on individual risk preferences, one can choose a suitable dynamic DCA strategy.

We have crafted three strategies—conservative, moderate, and aggressive—as starting points. An investor looking for less risk may want to wait for the risk to reach a very low point before starting to dynamically DCA-ing into the market. To reduce missing out on profits, such a risk-averse investor may begin selling the asset already when risk passes 50/100. On the other hand, an investor comfortable with more risk, might prefer investing into the asset until the risk reaches 60/100. The same investor may only start DDCA-ing out of the asset when the risk surpasses 80/100. The beauty of our framework lies in its adaptability to different preferences, providing a reliable strategy that proves itself over time. Below is an example of a moderate DDCA strategy based on the risk levels calculated by the model. The respective amounts to buy and sell for can be adjusted according to individual needs and risk tolerance.

4.3. Overcoming Inherent Risk

In the realm of assets like Bitcoin, the common understanding is that, given the limited supply, inflation of other fiat currencies, heightened scarcity due to halving events, and increased adoption, the fiatequivalent value should grow over time. This assumption, however, carries an inherent risk when applying traditional investment techniques such as Dollar Cost Averaging (DCA) or lump-sum strategies to Bitcoin.

If Bitcoin doesn't follow an upward trend, and instead moves sideways or even descends into fresh bear-market lows for a variety of reasons, the most common investment strategies usually generate negative returns. Our novel way of investing along with the model we have created allows returns on investing no matter what premise the underlying asset is given. We prove this in the following section.

Through our rigorous simulations, as detailed in this whitepaper, we present a dynamic DCA approach utilizing our risk model, which consistently yields positive results regardless of Bitcoin's price trajectory. This approach effectively eliminates the systematic risk associated with the hypothetical scenario of Bitcoin failing to exhibit long-term upward trends.

5. Proof of Profit

The importance of testing cannot be stressed enough when it comes to any tool meant to be used for investing or trading. A rigorous testing framework is must before the model can ever be considered viable for implementation. While some frameworks exist, most rely solely on backtesting the model using the same data it was trained on (Goebelbecker, 2023). Some frameworks extend their efforts to testing statistical significance and p-values for parameters. In our view, given the high volatility in the cryptocurrency realm, both approaches fall short. We firmly believe that testing should commence from the dataset stage and continue throughout every step of model development. To address this, we have devised our own testing framework, paying homage to bitcoin's cryptographic Proof of Work (PoW) by naming it Proof of Profit (PoP). PoP is built upon 3 fundamental steps:

1. Dataset Sourcing and Comparison:

The first step in our testing framework involves meticulous dataset sourcing and comparison. We understand the importance of utilizing reliable and diverse datasets, but also the challenges in avoiding biased data, mitigating the effects of multicollinearity, and addressing potential data gaps or inconsistencies.

2. Backtesting:

The backtesting process runs in parallel with finding the optimal dataset. This crucial step involves benchmarking our model against three widely recognized trading and investing strategies: HODL (Hold), DCA (Dollar-Cost Averaging), and a trend-following strategy.

3. Forward-testing, Simulations, & Stress Testing:

This is by far the most crucial step in assessing the viability of the model. This step involves subjecting our model to various simulated scenarios and stressful environments to evaluate its resilience and robustness. By simulating a very wide variety of future price trajectories such as mass bitcoin adoption, economic recessions, and more, we can assess how our model performs under adverse circumstances. The simulations are based on sound statistical models that respect the historical data in regards to trend and volatility.

By incorporating these three vital steps, we ensure that our model will perform across diverse market conditions. No matter if it is the bullish prediction of the influencer, or the pessimistic prophecy of the expert that turns out to be the lucky guess - The AlphaSquared risk model will perform.

5.1. Dataset Sourcing and Comparison

It is insufficient to simply select relevant data, test its effectiveness, and build the model. As perfectionists, we couldn't settle for anything less than exploring an extensive range of combinations. Hence, our model undergoes testing starting from the data selection stage.
We constantly ask ourselves: Which combination of datasets yields the most promising initial results while aligning with the economic fundamentals of markets and assets?

Furthermore, to overcome bias in the model, it is important to actively seek out complementary data. This means avoiding data selection that will lead to a model with high multicollinearity. We have observed that other models and trading strategies often suffer from this issue. While these models and strategies aim to achieve success by looking at confluence between variables, which is generally a good thing, they fail to account for multicollinearity. Consequently, their backtesting results may appear robust, incorporating numerous variables. However, many of these variables measure the same underlying factors. This can be compared to duplicating a single variable multiple times (Frost, 2017). We reduce such multicollinearity in our model by actively acknowledging the phenomenon and exploring the underlying factors that contribute to our data. As a result, we can identify essential variables and attributes to make up the ideal dataset.

While this may seem like an obvious approach to most data scientists, such an idealistic approach can also create bias-variance-tradeoff problems (Singh, 2018). Taking the aforementioned approach too far will undoubtedly result in a high bias and low variance classification model. This would lead to poor real-world applicability once the model is deployed. We predict that such overfitting concerns will be the greatest concern in the eye of the public for our model. Therefore, we have directed considerable attention and awareness to this issue all the way from the data collection process to final deployment. We will address any overfitting concerns from both a fundamental perspective in 5.2, as well as from a practical perspective in 5.3 by showcasing our custom-built simulation-and-stress-testing environment.

5.2. Overfitting and Fundamentals

Overfitting is a common pitfall in model development, where a model is excessively tailored to fit the training data, often at the cost of its predictive performance on new, unseen data (IBM, 2023). This typically occurs when a model is overly complex, such as having too many parameters relative to the number of observations. Overfit models tend to perform exceptionally well on the training data but poorly on the test data, as they capture the noise along with the underlying pattern in the training data. In the context of financial modeling, overfitting often manifests when models are built by indiscriminately selecting any available metrics and data, and optimizing for the combinations that yield the best backtesting results. While it is intuitive to identify metrics that have historically been good predictors of price, it is not guaranteed that these metrics will continue to perform similarly in the future.

To mitigate the risk of overfitting, our approach to data selection is grounded in fundamental analysis. We only consider using metrics and calculations that have a logical basis for influencing the asset's price. This approach ensures that our model is not merely curve-fitting to historical data but is capturing meaningful relationships that are likely to persist in the future.

In the next sections we will therefore not only cover backtesting results, but also prove the model's viability by forward testing based on various statistically sound price simulations.

5.3. Backtesting & Benchmarking

Even with the pitfalls previously described, backtesting is simply a must of any financial model. While it's far from perfect, it tells you something about the viability of the model. Backtesting in this context can reveal areas of weaknesses. In this stage of the build, we backtest the model and we also compare it to a benchmark HODL/DCA strategy, as well as a benchmark trend-follow strategy. Below is an illustration of how the models perform in the backtest on training data.

Note that the model was built and used in 2021 and 2022, but not made available to the public until Q2 of 2022.

While it's obvious the models perform very well in backtesting, we require some sort of benchmark to compare it to. As described in the framework of the model, particularly in 4.2, the model is supposed to be used in conjunction with the DDCA strategy we have devised. Therefore, we will benchmark the model against a traditional DCA strategy. In this context, the traditional DCA strategy is identical to the highly popular HODL strategy.

In addition, many might argue that the model should also be compared to traditional trading strategies based upon predicting or forecasting future market moves. We argue such strategies have little relevancy as they are not capable of consistently yielding profit. This is at the very least true for vast majority of both amateur and professional traders. A substantial body of research supports this fact. For example, a famous study by Barber et al. (2014) found that less than 3% of day-traders can predictably make profit, and other research suggests that number might be much lower. This does not include the bulk of amateur retail traders, implying that the true number is astronomically small. Furthermore, the efficient market hypothesis popularized by Princeton University economics professor Burton Malkiel in his 1973 book, "A Random Walk Down Wall Street," argues that since markets are informationally efficient, such strategies cannot be profitable. This theory has been successfully tested several times, one of the more popular tests was performed by the Wall Street Journal in 2019 where journalists picked stocks by means of throwing darts at a dartboard. The journalists' picks were pitted against the picks of some of the absolute elites of trading and investing. The results were evaluated after a year, and the journalists ended up winning. This is ofcourse not always true,, but it is a testimony proving that it is incredibly difficult, even for the best, to consistently predict market moves. Many seasoned investors who are aware of this fact, usually opt for a regular dollar cost averaging (DCA) strategy instead. This removes the component of predicting market moves, and instead only requires the asset to be valued at a higher price sometime in the future, at an unspecified point in time. Therefore, we argue that a DCA strategy is the most competitive benchmark to compare our framework against. Both from a technical, and from a usage standpoint, being the most frequently applied strategy to asset investing.

Regardless of this, to put speculations to rest concerning how the framework performs against an active trading strategy, we will also benchmark the framework against a trend following strategy. Swing trading based on trends is perhaps the most well-known and popular investment strategy, making it a good candidate for benchmarking.

5.3.1. Benchmarking General Parameters

First, let us construct a general framework with parameters that will apply to all benchmark strategies. We decide on a fixed amount of fiat currency to be added to our trading account on a fixed time interval. Since investing on a monthly basis is a popular choice, we pick $1 000 to be transferred each 30 days. This capital will be used to invest using each of the benchmark strategies.

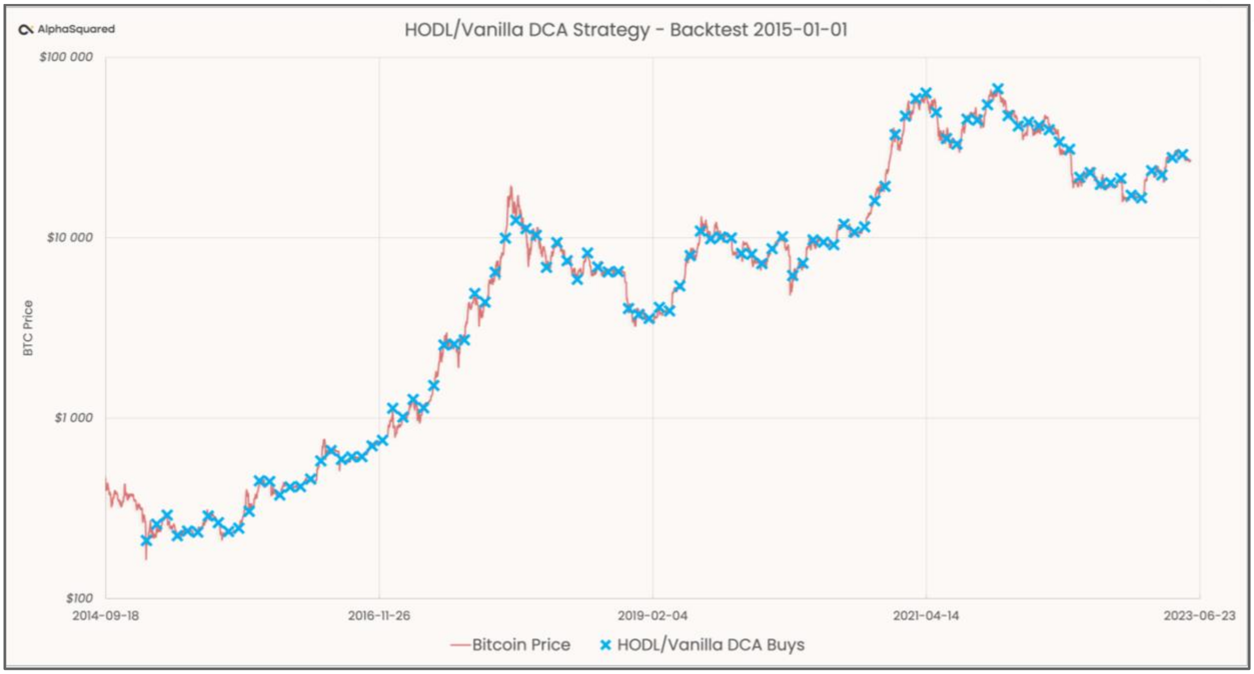
Total Amount to be added to trading account each 30 days: $1.000

Starting date: 2015.01.01.

End Date: 2023.05.27

5.3.2. DCA/HODL Strategy Benchmark

Allow us to establish a baseline benchmark with the HODL or vanilla DCA strategy. The HODL strategy ("HOLD" misspelled, but also an acronym for "Hold On for Dear Life") is a highly popular and well known strategy among retail investors, both in TradFi, as well as cryptocurrency. It simply involves investing into an asset, but never selling any of it, regardless of how the market performs. For this benchmark, as $1.000 are added to the trading account monthly, we will purchase Bitcoin for $1.000 on a monthly basis indefinitely. The result of this strategy is illustrated below.



HODL / Vanilla DCA Strategy

BTC Final Holdings	*80,92*
BTC Price	*$26 857*
Total Dollar Amount Invested	*$102 000*
Cash Balance	*0*
Profit	*$2 071 166*
Profit in Percent	*2 031%*

*Percentages might differ from real values due to rounding

Since its inception, Bitcoin has experienced unprecedented growth, which has enabled the Dollar Cost Averaging (DCA) strategy to deliver an impressive return on investment (ROI) of +2,031%. However, it's worth noting that this analysis assumes the DCA strategy commences at the absolute bottom of a bear market, which significantly optimizes its results.

Furthermore, we must consider the cyclical nature of cryptocurrency markets and the typical surge of new investors during a bull run. This scenario often encourages investors to adopt the DCA strategy when prices are exceedingly high. Consequently, these investors usually find themselves in a state of loss, having to lower their average cost basis over several years before finally reaching a break-even point.

As we will discuss in the subsequent benchmarks, implementing a Dynamic Dollar Cost Averaging (DDCA) Strategy, guided by our risk metric, can help protect investors from the risks associated with entering the market at high points. More importantly, the DDCA strategy has the potential to significantly outperform the traditional DCA strategy in terms of returns.

5.3.3. Trend-Follow Strategy Benchmark

We will now set a secondary benchmark using a widely adopted trend-following trading strategy involving the 50-week moving average. This moving average is frequently utilized by investors to discern whether an asset is experiencing an uptrend or a downtrend. The strategy is straightforward yet renowned for its efficacy.

Essentially, an investor initiates purchases when the asset's price surpasses its own 50-week moving average, signaling an upward trend. In contrast, the investor offloads the asset when the price falls below the 50-week moving average, indicating a downward trend. We will present the outcomes of employing this strategy in the following section.

Trend-follow Strategy

BTC Final Holdings	*109,2*
BTC Price	*$26 857*
Total Dollar Amount Invested	*$103 000*
Cash Balance	*0*
Avg Profit	*$2 829 836*
Profit in Percent	*2 800%*

*Percentages might differ from real values due to rounding

The trend-following strategy results in a superior return on investment compared to the standard Dollar Cost Averaging (DCA) strategy. It's intriguing to note that despite this strategy's simplicity and higher returns, DCA is more widely adopted. We believe this preference may stem from the ease of application that the DCA approach offers.

The trend-following method generates a profit of 2,800%, which is 37.8% greater than the return provided by the simple DCA strategy.

5.3.4. The Risk Model DDCA Strategy Benchmark

We will now introduce the benchmark for the Dynamic Dollar Cost Averaging (DDCA) strategy. The DDCA method employs the same foundational parameters as the HODL/DCA strategy, which involves transferring $1,000 to the trading account every 30 days. The primary distinction lies in the use of our risk model, which will guide the amount we decide to buy or sell.

Initially, we need to determine what portion of our fiat account's capital we want to invest at a given risk level. Following that, we must ascertain how much of the obtained asset we intend to sell at that same risk level. Here's how the DDCA strategy will unfold:

DDCA Strategy	*Buy Threshold A*	*Buy Threshold B*	*Sell Threshold A*	*Sell Threshold B*
Risk	0 - 5	10-30	70	95
Percentage of Available Capital to Invest	75%	25%	-	-
Percentage of Acquired Asset to sell	-	-	25%	75%

If the Risk level falls within the range of 10-30, we utilize 25% of our accumulated cash capital to buy into the market. However, if the Risk drops between 0-5, we mobilize the residual capital to fully invest in the market.

On the flip side, if the Risk level exceeds 70, we liquidate 25% of the asset to convert into cash capital. If the Risk further escalates beyond 95, we proceed to sell the remaining 75% of our asset reserve, again, for cash.

While this is a general guideline, we advise a more flexible approach in practice (and provide such approach models under our strategies section), distributing the investment and divestment into smaller fragments to align with a wider spectrum of risk levels. This simplification serves well for backtesting purposes. The ensuing chart will demonstrate how an investor would have transacted in Bitcoin following this strategy.

DDCA Strategy Based on Risk Levels

BTC Final Holdings	*481,57*
BTC Price	*$26 857*
Total Dollar Amount Invested	*$103 000*
Cash Balance	*$4 625*
Profit	*$12 835 119*
Profit in Percent	*12 561%*

*Percentages might differ from real values due to rounding

Though all three strategies invest nearly identical sums into the market, the Dynamic Dollar Cost Averaging (DDCA) strategy, utilizing the risk model, greatly surpasses both the HODL/Vanilla DCA and the trend-following strategies. When compared to the HODL/Vanilla DCA method, the DDCA strategy garners over six times the profit.

While backtesting serves merely as an indicator of a model's performance, both benchmark strategies behave as expected. However, the DDCA strategy, grounded on our risk model, decisively outperforms both with a significant margin.

Beyond the overall profit, this strategy also shields novice investors from the often-costly mistake of buying in when prices are at their peak, a common misstep during a bull run. None of the other strategies we compared effectively safeguard against the seasonality characteristic of the crypto market.

5.4. Forward-testing, Simulations, & Stress testing

Backtesting is often frowned upon due to overfitting concerns, which is a very legitimate concern. Just because a model backtests well, there is little evidence to suggest it will perform as well on untrained data. To thoroughly challenge our model's capabilities, we subjected it to simulations featuring diverse price trajectories spanning the next 2 years. We argue that forward testing using a large set of simulated realistic price trajectories, should be the go-to for investors and data scientists seeking a genuinely honest and objective evaluation of their model and strategy.

Furthermore, recent events like the pandemic have taught us that no matter how unlikely they may seem, black swan events do happen. This means that the volatility of an asset can far exceed its normal range. Such large random events can only be truly tested in a simulation-type environment. Therefore, we decided that the simulations must contain price action that puts the model under stressful conditions, ensuring it holds up during times of high volatility. As a result, we impose a criterion for our simulations to surpass a given threshold of volatility.

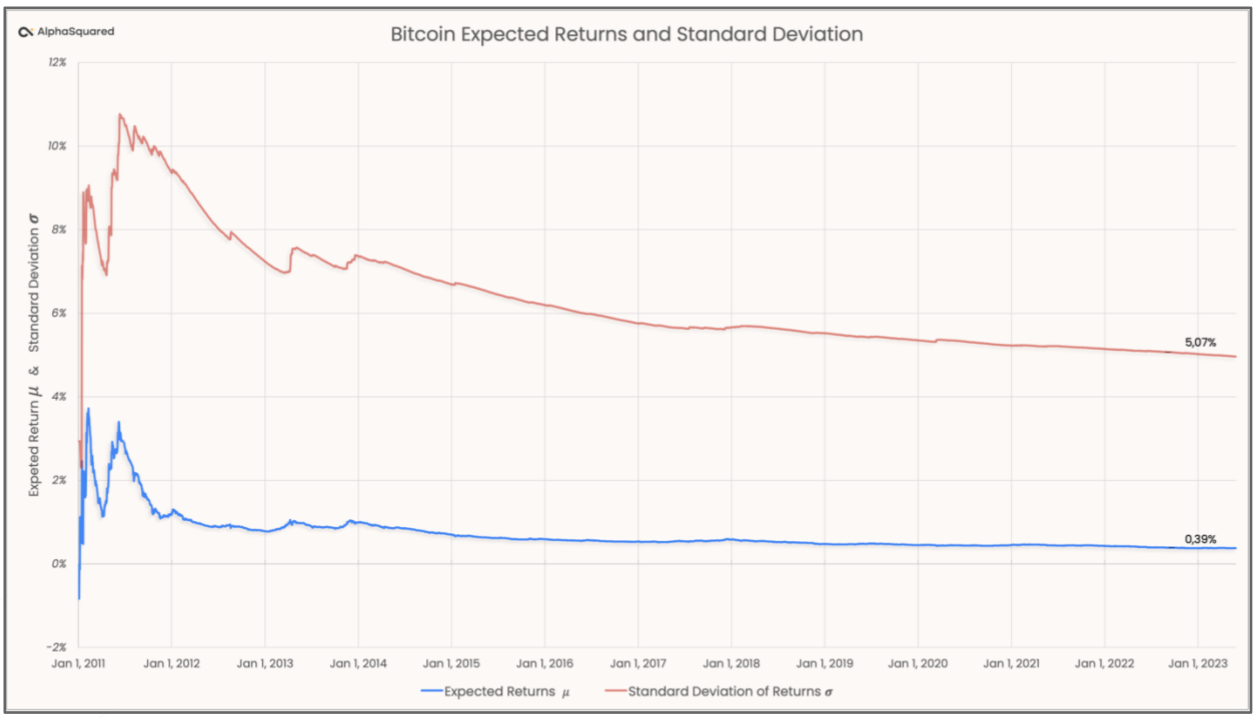
5.4.1. Simulation Fundamentals and Assumptions

The price of a stock, or crypto, can be characterized as a stochastic process where the change in price at time t is independent of the change in price at t-1 (Liu, 2019). By means of a few computations and basic assumptions, we can simulate the price of an asset for any desired time period. To begin with, in the case of bitcoin, we assume a constant drift and volatility. In the context of financial modeling, drift can most easily be defined as the average daily return of the asset. Furthermore, we assume that the returns of bitcoin fit a normal distribution. It is important to acknowledge the presence of "fat tails" in the historical distribution of bitcoin returns. Fat tails refer to the occurrence of extreme events with higher frequency than what would be expected under a normal distribution (Roh, 2020).

Through our research, we determined that an acceptable simulation for model testing must encompass volatility that exceeds at least 3 standard deviations from the mean, equating to beyond the 98.76th percentile. This does to some extent deal with the issue of fat tails. Despite the fat-tail phenomenon, the consensus is that a normal distribution is a very close approximation of the true distributions. With these aspects in mind, we can demonstrate how the price of bitcoin can be simulated.

5.4.2. Estimation of Parameters

First, we must compute the standard deviation and expected daily returns of bitcoin. We assume a constant drift and volatility, however, the means of estimating these numbers is not a given. We know that the price of bitcoin is heavily characterized by seasonality. Furthermore, we also know that both the volatility and returns of bitcoin are diminishing as a product of time and asset growth. As an asset grows over time, it will generally become less and less volatile, following a logarithmic pattern from new to seasoned asset. In case someone might doubt these assumptions, we can plot the standard deviation and expected returns of bitcoin over time to illustrate this fact:



We note that average daily returns and standard deviations are diminishing over time, which is in line with what we would expect. Of course, there are always *force majeure* events which can alter the course of both the expected return and standard deviation. Such events will not be considered. Through computational efforts based on historical data and the assumption of diminishing returns and volatility, we can estimate the average daily return and standard deviation for our simulations.

5.4.3. Calculation of Returns

The return at time $T(R(t))$ is calculated as follows:

$$R(t) = \mu + \sigma * Z$$

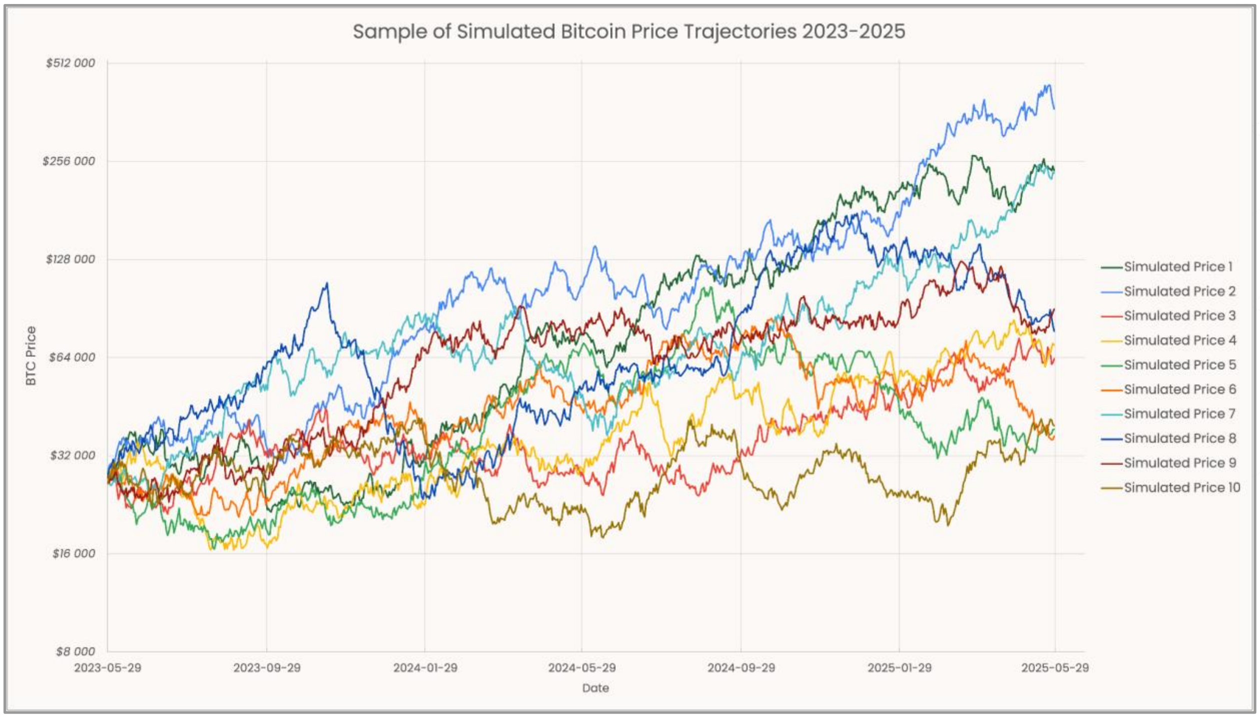
where:

- μ is the drift, representing the expected return or mean of the returns.
- σ is the volatility, representing the standard deviation of the returns.
- Z is a random number from a standard normal distribution (mean 0, standard deviation 1) which goes by the following formula: $f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2}$

5.4.4. Application of Returns to Asset Price

Considering we start with an initial asset price of P_t , subsequent prices P_{t+1} are calculated by applying each return $R(t)$ to the previous price so that: $P_{t+1} = P_t * (1 + R(t))$

Through this approach we can easily simulate thousands of price trajectories for bitcoin for a fixed time interval. In this case, we have chosen to simulate price trajectories from *May 29th 2023* to *May 29th 2025*. This means our starting price is roughly $27.000, which is the price on *May 28th 2023*. Below is a chart of 10 randomly sampled price trajectories for the chosen time period.



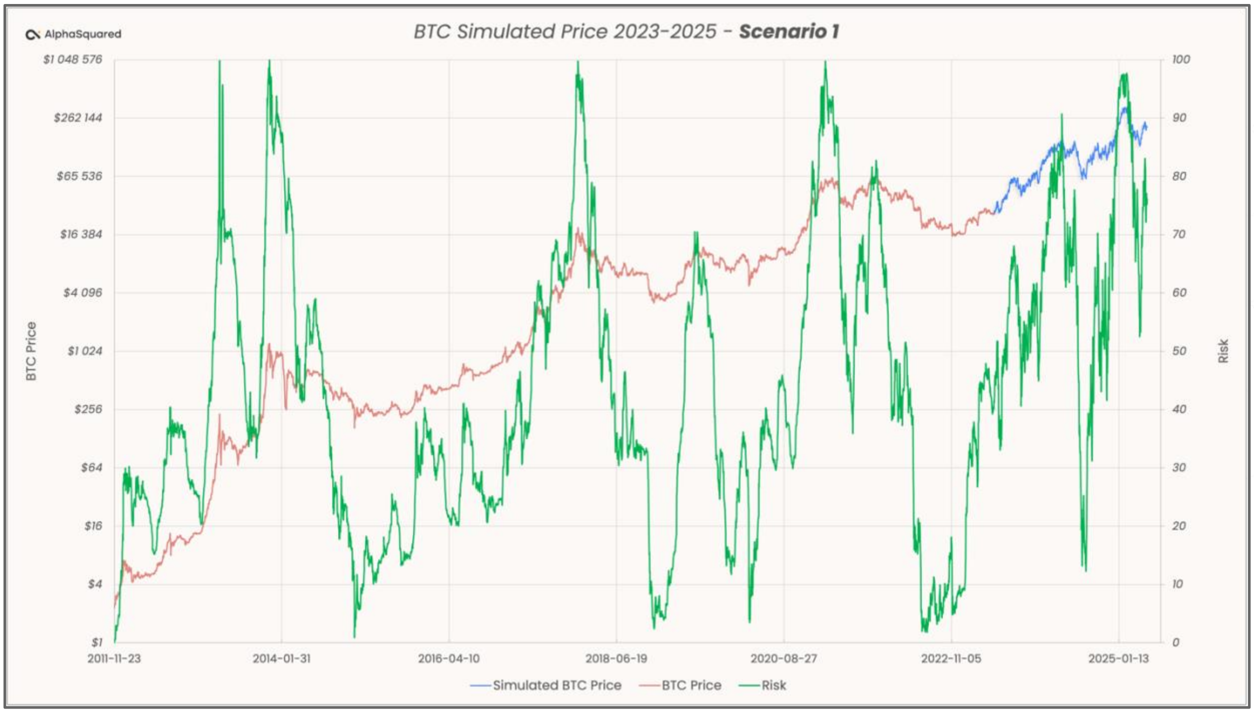
It is important to note that these trajectories are not predictions, but rather possible trajectories from a statistical standpoint. These simulations are a very close approximation to the price action of bitcoin, and they are therefore suitable to use for forward-testing our model in specific scenarios to see how well it performs.

In our testing, we deliberately choose to test the model on simulations based upon 3 criteria.

1. They must somewhere in the price path contain volatility of at least 3 standard deviations from the mean.
2. They should represent a variety of economic circumstances ranging from and including scenarios such as substantial BTC adoption to economic recession.
3. The simulation must be considered somewhat reasonable. This means that price trajectories that are very clear outliers are neglected.

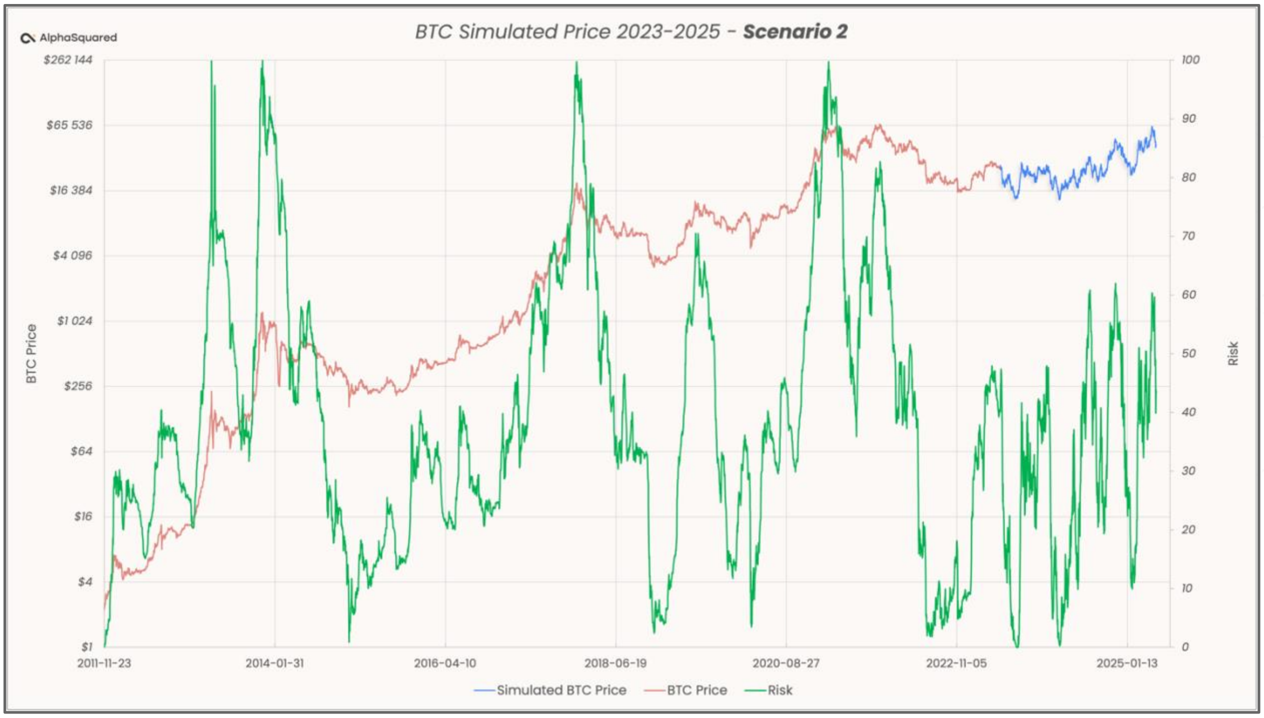
The next section contains a sample of three randomly chosen price trajectories that fit these criteria.

5.4.5. Simulation & Forward-testing Results



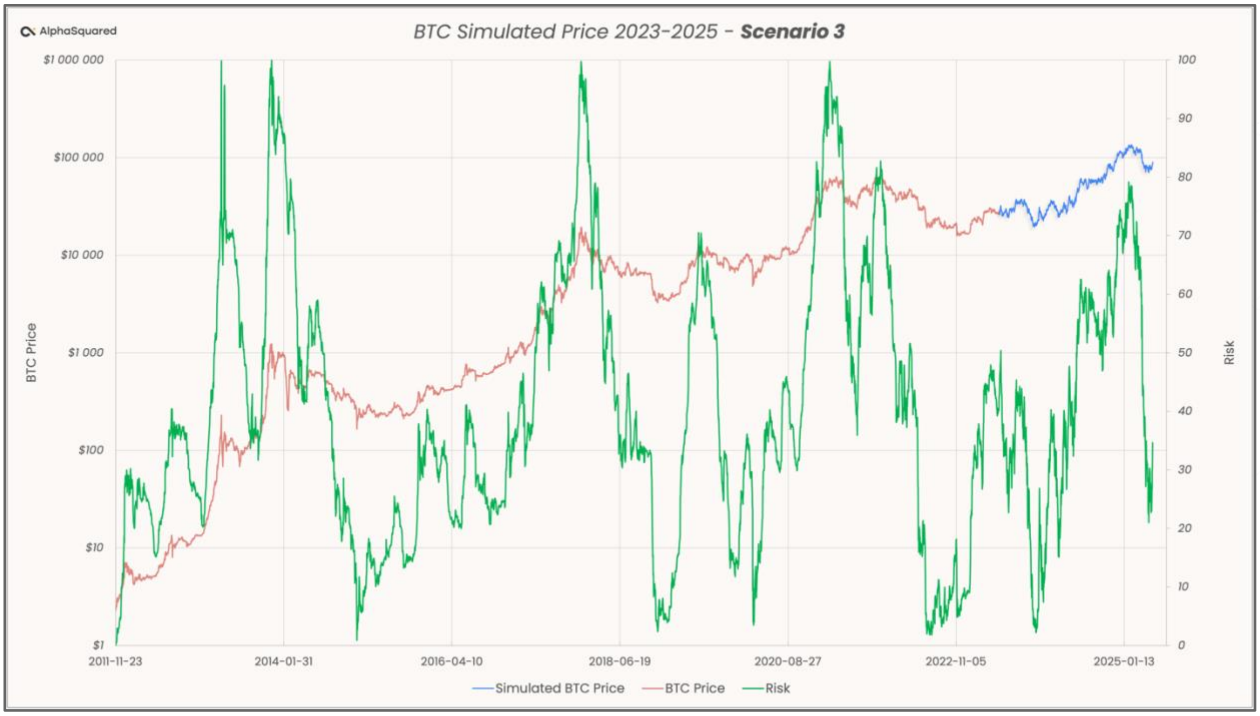
Scenario 1 displays a scenario in which Bitcoin is set to have another bull run - something in accordance with the popular "cycle theory", reaching new all-time-highs of 328'000$ by 2025. This case represents the most popular and anticipated scenario from a public perspective.

The test results show extreme effectiveness for a DDCA investing strategy thanks to the high accuracy of the model's risk valuation. Even with a quite aggressive risk profile of only selling above 90 Risk, this metric would have performed excellently in a bull-market scenario.



Scenario 2 displays the opposite scenario compared to scenario 1. In this possible price trajectory, we can hypothesize that the world economy has been suffering from a recession. The BTC price action has been a crab walk for 2,5 years with a new major low of $13 514. Eventually the price reaches roughly $62 000 dollars in May of 2025, slightly lower than the previous ATH of $69 000 in 2021. This is an unpopular and not highly anticipated trajectory.

Nonetheless we deem it perfect to illustrate the model's profitability regardless of trend trajectory. Even though bitcoin did not reach a new all-time high in this scenario, using the risk model would still have yielded significant profits. An investor following a DDCA strategy based on risk levels, would have a portfolio in profit with a significant BTC stack on hand at an extremely low average cost price. The precise outcome would depend on the exact DDCA strategy chosen of course.



In scenario 3, we witness somewhat of a middle way between scenario 1 and 2. In this price trajectory, bitcoin is continuing its crab walk and reaches another low of $19 628 in late 2023. We see the start of a new bull run in May of 2024, eventually reaching a new lukewarm ATH of $135 103 in May of 2025.

Using the risk model would have an investor buy a significant stack of bitcoin at around $19 000, only to start selling above 50 risk ranging from $60 000 all the way up to $135 103 corresponding to 80/100 risk. Comparing this to a DCA or Trend-follow approach, using the model in a scenario with lower volatility still yields exceptional results.

5.4.6 Conclusion of Simulation & Forward-testing Results

The three simulation scenarios provide a comprehensive view of Bitcoin's potential trajectories through 2025, showcasing the spectrum from bullish to bearish market conditions, and various points in-between. Despite the differing outcomes in each scenario, one consistent result emerges: the robustness and profitability of using the risk model for a Dynamic Dollar Cost Averaging (DDCA) investing strategy.

In Scenario 1, a bullish market and Bitcoin's all-time high illustrated the impressive efficiency of the DDCA strategy, maximizing returns in a rising market. In Scenario 2, even with Bitcoin not reaching a new all-time high and remaining somewhat stagnant, the risk model-driven DDCA strategy allowed for profitability and an impressive accumulation of Bitcoin at an extremely low average cost price. Scenario 3, representing a less volatile market, still demonstrates that the DDCA strategy outperforms traditional DCA or trend-following approaches, successfully capitalizing on market conditions for profitable investing.

These simulations illustrate the adaptability and robustness of the DDCA strategy in various market scenarios. Regardless of Bitcoin's price action, the risk model effectively manages risk levels, thereby improving overall portfolio performance.

6. Vision

At AlphaSquared, we envision a future where all investors, regardless of their level of experience, can confidently navigate the unpredictable world of financial markets with realistic expectations. There is a prevalence of opportunistic actors who prey on investors' ambitions by offering empty promises and underwhelming financial products such as courses, trading signals, and e-books - or providing make-believe predictions to gain a following of their own. Having personally navigated these hurdles, we understand the struggles of the modern investor. That's why our mission is more than just a business goal—it's personal. We aim to empower investors with the tools and knowledge necessary to avoid such pitfalls.

With AlphaSquared, investors can expect a data-driven approach and a focus on setting realistic expectations, rather than being lured by false promises and daydreams. Central to our philosophy is the belief in a reactionary approach to investing, acknowledging that while markets are largely unpredictable, they can be tactfully responded to. All you need is the right tool, and the right strategy.

Our unique selling proposition lies in our innovative, user-friendly framework. We cut through the complexity of investing by integrating all necessary data and indicators into a single, intuitive metric. This approach paves the way for a straightforward, data-focused perspective, devoid of unnecessary distractions.

At the core of our mission is fostering a community of investors who are ready to adopt a completely new dogma when it comes to investing and trading. This paradigm shift holds the potential to send ripples through the world of investing, positioning AlphaSquared and our community at the forefront of this movement. We aim to be pioneers in investing, and our future platform will reflect this ambition. We envision a platform with a wide variety of cutting-edge risk identification models, corresponding tailored strategies, and an engaged community committed to sharing and improving this new user-friendly and pragmatic approach to investing.

7. Conclusion

AlphaSquared offers a fresh perspective on navigating the often-volatile financial markets, particularly within the world of cryptocurrencies. The core of our strategy revolves around classifying and reacting to real-time market conditions and involves a tailored approach that adapts to individual investors' needs and risk tolerance. This strategy involves two key components: the Model Framework and the Strategy Framework.

The Model Framework harnesses a combination of traditional statistical models, asset growth models, technical analysis techniques, and our custom algorithms to categorize current market conditions. On the other hand, the Strategy Framework incorporates a Dynamic Dollar Cost Averaging (DCA) method that adjusts the size of recurring investments based on model-calculated risk.

To ensure the robustness of our strategy, we've established a rigorous testing framework known as Proof of Profit (PoP). This includes dataset sourcing and comparison, backtesting, simulations, and stress testing/forward testing. Our testing results show that the Dynamic DCA strategy, underpinned by the AlphaSquared risk model, consistently outperforms traditional DCA/HODL strategies, as well as a more active trend-follow strategy by a very significant margin. Furthermore, our forward-testing simulations revealed the true efficiency of the metric and the DDCA strategy in a variety of possible future market scenarios.

We recognize the harsh realities of the market, and that if you cannot beat someone on their own court, you need to switch to a new court. AlphaSquared embodies this realization, offering a remarkable solution and completely new approach to investing and trading. By leveraging our highly sophisticated risk classification system, implemented through our elegant DDCA strategy, beating the market is no longer an elusive dream, but an attainable reality.

References

1. Barber, B. M., Lee, Y.-T., Liu, Y.-J., & Odean, T. (2014). Do Day Traders Rationally Learn About Their Ability? SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2535636

2. Jakab, S. (2019, May 6). Making Monkeys Out of the Sohn Investing Gurus. Retrieved June 14, 2023, from WSJ website: https://www.wsj.com/articles/making-monkeys-out-of-the-sohn-investing-gurus-11557115260
3. Malkiel, B. G. (1973). A Random Walk Down Wall Street: The Time-Tested Strategy for Successful Investing. W. W. Norton & Company.
4. Liu, X. L. (2019). Stochastic Process and its Role in The Development of the Financial Market: Celebrating Professor Chow's Long and Successful Career. *Communications on Stochastic Analysis*, *13* (3). https://doi.org/10.31390/cosa.13.3.07
5. Srushti Dongrey. (2022, April 30). Study of Market Indicators used for Technical Analysis. Retrieved June 15, 2023, from ResearchGate website: https://www.researchgate.net/publication/360497413_Study_of_Market_Indicators_used_for_Technical_Analysis
6. Team, C. (2020, August 14). Dollar-Cost Averaging (DCA). Retrieved June 12, 2023, from Corporate Finance Institute website: https://corporatefinanceinstitute.com/resources/wealth-management/dollar-cost-averaging-dca/
7. Goebelbecker, E. (2023, March 12). Python Backtesting Frameworks: Six Options to Consider. Retrieved June 20, 2023, from Pipekit.io website: https://pipekit.io/blog/python-backtesting-frameworks-six-options-to-consider

8. Frost, J. (2017, April 2). Multicollinearity in Regression Analysis: Problems, Detection, and Solutions. Retrieved June 21, 2023, from Statistics By Jim website: https://statisticsbyjim.com/regression/multicollinearity-in-regression-analysis/
9. Singh, S. (2018, May 21). Understanding the Bias-Variance Tradeoff - Towards Data Science. Retrieved June 19, 2023, from Medium website: https://towardsdatascience.com/understanding-the-bias-variance-tradeoff-165e6942b229
10. What is Overfitting? | IBM. (2023). Retrieved June 23, 2023, from Ibm.com website: https://www.ibm.com/topics/overfitting
11. Roh, H. (2020, June 17). What is Fat Tail? | Towards Data Science. Retrieved June 23, 2023, from Medium website: https://towardsdatascience.com/journey-to-tempered-stable-distribution-part-1-fat-tailed-distribution-958d28bc20c