AlphaSquared Whitepaper

A Model and Strategy Framework

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Executive Summary

This paper introduces AlphaSquared, a novel investment approach centered on classifying and reacting to current market conditions rather than attempting to predict future trends. At its core, AlphaSquared combines a Model Framework and a Strategy Framework to empower investors with tools tailored to their needs and risk tolerance.

The Model Framework is built upon asset-specific machine learning models trained on tailored data, utilizing input factors ranging from asset growth patterns to technical indicators, sentiment, and macroeconomic variables. These inputs are used to generate a precise 0-to-100 risk classification score. This risk metric informs the Strategy Framework, which includes a Dynamic Dollar Cost Averaging (DCA) method that adjusts investment sizes based on the calculated risk. This strategy allows investors to allocate more capital during low-risk periods and less during high-risk periods, optimizing both returns and risk management.

To ensure the reliability of this framework, we developed a validation framework that includes dataset evaluation, backtesting (on real, non-back-fitted data) against traditional approaches like HODL and regular DCA, and forward-testing through simulations. Results consistently show that AlphaSquared's Dynamic DCA strategy outperforms conventional methods, achieving higher profitability with reduced portfolio volatility.

1. Introduction

The financial markets today are filled with services claiming to help traders generate profits by predicting market movements. Despite evidence showing that these predictions often fail, many investors continue to seek out these services, believing forecasting is essential for success. However, we believe this approach is fundamentally flawed.

At AlphaSquared, we offer a different solution. Instead of trying to predict the market, we focus on classifying current market conditions to help investors make informed decisions. Our approach empowers retail investors by providing a snapshot of current market conditions paired with strategy-building tools, offering simplified access to critical metrics without overwhelming them with excessive data.

In this paper, we introduce AlphaSquared's approach and explain how our models classify market risk using quantitative analysis. We will also describe the testing framework that ensures the robustness of our model and share our vision for transforming how retail investors engage with financial markets.

2. The Problem

Traditional investing methods relying on predictions often fall short. The core issue is the unpredictability of the market, which makes it difficult for retail investors to consistently and profitably predict market trends. Predictive models fail to account for the disparity in resources between retail investors and institutional players, leading to poor outcomes. We have experienced the failure of these models firsthand, particularly during mania-driven or bubble-driven rallies, such as Bitcoin bull runs in 2017 and 2021, or the marijuana boom in the Canadian stock market in 2016.

We propose a new approach: classifying and reacting to current market conditions rather than attempting to predict future movements. This method empowers retail investors to make informed decisions based on objective, real-time data, acknowledging the unpredictable nature of markets.

Our classification approach aligns with the Efficient Market Hypothesis, which asserts that market prices reflect all available information, making consistent prediction unreliable. By embracing a reactionary rather than predictive strategy, AlphaSquared offers a more effective solution for navigating financial markets.

3. The Proposed Framework

Our approach revolves around two core components: the Model Framework and the Strategy Framework.

The Model Framework uses machine learning to analyze data from various sources, including price action, sentiment, on-chain metrics, macroeconomics, and more, providing real-time insights into current market conditions.

The Strategy Framework helps investors construct a personalized risk-based investment strategy similar to DCA. Based on insights from the Model Framework, it helps optimize investment decisions according to personal preferences, offering a more effective and tailored approach compared to standard DCA or 'Buy and HODL'.

Together, these frameworks offer a practical, data-driven way to navigate financial markets, helping investors make informed decisions without overwhelming complexity.

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 Framework

A fresh approach to data analysis is essential for emerging assets. Our goal is to develop robust, machine learning-driven models that excel at precise real-time risk classification of cryptocurrency assets, and eventually stocks. By leveraging machine learning, we can analyze a vast array of data points that would be impossible for a human to process effectively. This allows us to consider numerous market factors and extract meaningful insights in real time, using raw, unfiltered data to minimize biases and assumptions.

4.1.1 Asset-Specific Models with Proven Track Record

Each model we develop is individually trained and tailored, taking into account the specific fundamentals of each asset. The purpose is to ensure a high degree of specificity and accuracy in capturing its unique dynamics. For assets with limited data availability, we employ a sophisticated approach where the models may be partially trained on similar assets or asset groups. This approach differentiates our model from others by providing robust, asset-specific risk assessment. This is largely what explains the high degree of accuracy compared to other predictive and classification models, as our model has been operational for four years with consistently strong performance.

4.1.2 Machine Learning

Our models generally rely on feed-forward neural networks for classification, an approach particularly suited to capturing nonlinear relationships. Off-the-shelf machine learning models can be effective, but we have fine-tuned their performance by incorporating custom activation functions and techniques, such as tailored weight adjustments. The training process, whether supervised or unsupervised, is a key aspect of our proprietary framework and remains confidential. We understand that this is a point of interest, but it is also a critical part of our competitive advantage. While the algorithms themselves are fairly standard, there are components in defining and training the models which involve a high degree of creativity that we are proud of. This has directly contributed to the high level of accuracy and performance we have demonstrated over the past four years.

4.1.3 Input Factors

Our philosophy around input selection is that it's not just about what data you choose to include, but equally about what you choose to exclude. We spend considerable time and resources on selecting the right data, drawing on domain expertise to ensure every input is fundamentally sound.

We understand that many are curious about what goes into our model. For a model like ours to retain value, it must build a track record, which takes time. Our model framework now has a proven 3+ year track record, and revealing all input factors would allow others to bypass the years of trust-building and work we have done. This would not be fair to us or our early-bird members. Therefore, the full inputs of the model remain proprietary. However, some examples of inputs include the following:

- **Asset Growth Models**: We incorporate asset growth models to capture the unique growth patterns and trends specific to different cryptocurrencies.
- **Price, Volatility, Sentiment, On-Chain, and Macroeconomic Data:** We leverage price data, volatility, volume, statistical patterns, and some technical indicators as inputs to classify risk. Sentiment, on-chain metrics, and macroeconomic factors are also considered, though their influence may vary depending on the asset.
- **Black Swan Events & Market Adoption:** The model is trained to account for Black Swan events and adapt to the market adoption of assets. This ensures that unexpected events and evolving adoption rates are considered in the risk assessment process.
- **Custom Indicators:** In addition to the above-mentioned factors, we have developed custom indicators that were built years prior to the risk model. These indicators were incorporated during the model's creation to enhance its classification capabilities.

4.1.4 Variables That Are Not Inputs Factors

When building models, it can be tempting to include as many variables as possible to improve the fit during testing. This approach might allow for impressive initial results; however, it can undermine the model's long-term accuracy and reliability. We evaluate the inclusion of variables through fundamental analysis to ensure the model's long-term reliability and accuracy.

As part of this philosophy, we deliberately omit variables that could increase initial performance but pose significant risks long-term. These risks typically fall into three categories:

1. **Easily Manipulated:** Variables susceptible to third-party manipulation can lead to unreliable classifications.

2. **Easily Stripped:** Data sources that could easily be revoked or restricted by third parties without being replaced threaten the model's continuity.
3. **Short-Term Influence:** Metrics that might impact the risk of an asset today but lose relevance in the future.

For example, consider Google keyword search data. At first glance, this seems like a valuable input. However, such data is highly susceptible to algorithm changes by Google, which is renowned for frequently modifying its algorithms. Additionally, cultural shifts in how people search for and discuss assets can impact the relevance of this data. For instance, if Bitcoin becomes mainstream, users may stop searching for terms like "Bitcoin" or "BTC". It may be unlikely you would hear someone say "send me 0.00004 BTC" instead of simply saying "send me 4000 sats" or other colloquial phrases. These evolving dynamics make reliance on such variables risky and potentially unreliable over time. These changes could render the data obsolete, making a model trained on such data lose a lot of its reliability. To mitigate these risks, we exclude such variables from our models, prioritizing long-term sustainability over short-term gains. This is simply a rudimentary example of the reasoning that underpins what variables we choose to include and exclude.

4.1.4 Self-Learning Mechanism and Maintenance

The model includes a self-learning mechanism that operates independently after its initial launch, without manual adjustments or fine-tuning from us. Since inception, the model has been untouched, ensuring that no subjective biases affect its performance. It continuously takes in new data daily and re-estimates some of its parameters to stay aligned with recent market conditions. This mechanism allows the model to remain highly responsive to evolving market realities.

Historical data, as shown in our charts, is always preserved, ensuring that the model's past classifications are accurately reflected without any retroactive changes. This means that each data point reflects the true value and state of the model at that specific time.

4.1.5 User Interface and Risk Assessment

Our user-friendly interface presents the model's output in a simplified form. The result is a risk assessment score from 0 to 100, where 0 represents minimal risk and 100 signifies maximum risk. This straightforward interface enables investors to make informed decisions without being overwhelmed by complexity.

4.2 Strategies

With the model in place, it is essential to design a strategy compatible with its workings. Dollar cost averaging (DCA) involves purchasing an asset regularly, such as weekly, to mitigate volatility and risk (CFI, 2020). However, this approach reduces potential profits and increases the risk for severe drawdowns. To address this, we propose Dynamic Dollar Cost Averaging (DDCA), which adjusts recurring investment sizes based on the model's risk calculation. As risk decreases, the dollar amount invested increases, and as risk rises, more of the asset is sold. A risk level of 50/100 is an example of a natural cutoff point, though risk-averse investors may prefer earlier thresholds, while higher-risk investors might aim for later ones.

We provide three template strategies—conservative, moderate, and aggressive—designed for varying risk tolerances. Buying may occur only at low or up to high risk levels, while selling may begin earlier or later, depending on individual preferences.

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 Risk Model levels. The respective amounts to buy and sell for can be adjusted according to individual needs and risk tolerance.

4.2.1 Overcoming Inherent Risk

Bitcoin's limited supply, fiat currency inflation, scarcity from halving events, and adoption suggest its value should grow over time. However, this assumption carries risks when using traditional strategies like DCA or lump-sum investing. Emerging assets rarely increase linearly but often experience periods of under- and overvaluation. In such cases, DCA or lump-sum investing carries greater risk.

Our approach aims to capitalize on these risk-on and risk-off periods, allowing for better returns while remaining agnostic to the market regime.

4. Validation Framework

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 of these 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 Risk Model will perform.

5.1 Dataset Sourcing and Comparison

Simply selecting and testing relevant data is not enough. We rigorously evaluate a wide range of dataset combinations to identify those that yield the best 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, in reality, 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 are able to 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

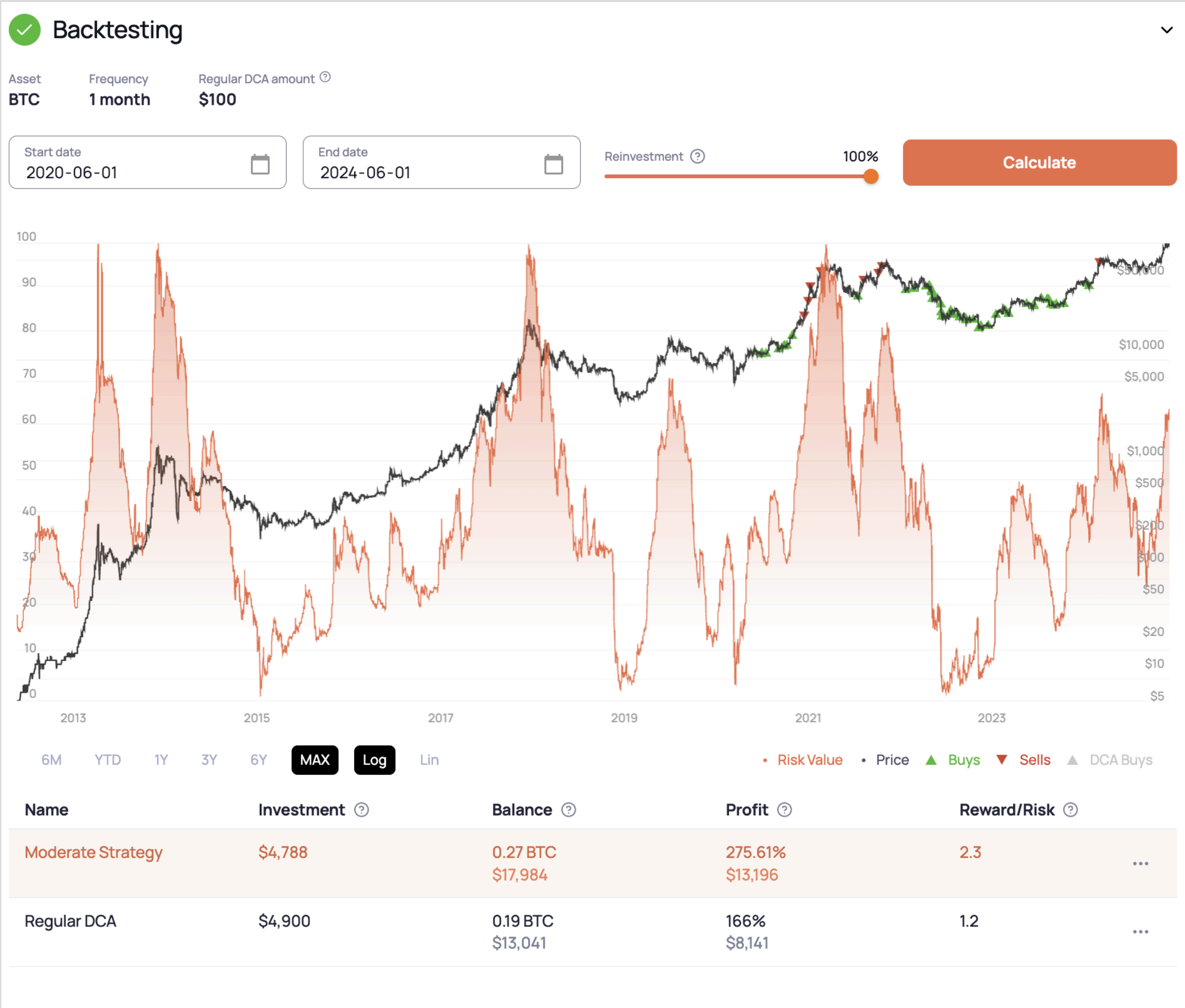
Even with the pitfalls previously described, backtesting is a must for any financial model. While it's far from perfect, backtesting provides valuable insights into the model's viability and can highlight areas of weakness.

Below is an example of a backtest performed between June 1, 2020, and June 1, 2024. In this case, the benchmark is a regular DCA strategy that invests $100 monthly over this period. In comparison, our moderate risk-based strategy distributes the same $100 across risk levels as follows: $179 at risk levels 0-10, $134 at 10-20, $89 at 20-30, and $45 at 30-40. This approach invests more at lower risk levels and progressively less as risk increases.

Selling is similarly distributed: 10% of the accumulated asset is sold at risk 60, 20% at risk 70, 30% at risk 80, and 40% at risk 90. This ensures the strategy adjusts dynamically to market conditions, allocating capital and assets based on calculated risk. Reinvesting is set to 100%

to reflect that after selling, an investor would not want to start “from scratch” by leaving all their previously invested capital on the sidelines.

IMPORTANT: 75% of the data used in this backtest comes from real risk outputs generated by the model during its operation, not back-fitted data. Hence this is not a backtest in the traditional sense people are used to seeing them, where a strategy is tested on a recently fit model. We are also testing a real strategy that has existed since the model's inception, meaning these results are very close to what you would have achieved had you discovered us three years ago and followed one of our strategies.



The findings from this backtest reveal the significant advantage of our moderate risk-based strategy compared to a regular DCA approach:

Strategy	Investment	BTC Balance	Portfolio Value	Profit	Reward/Risk
Moderate Strategy	$4,788	0.27 BTC	$17,984	275.61%	2.3
Regular DCA	$4,900	0.19 BTC	$13,041	166%	1.2

Our moderate strategy significantly outperformed regular DCA, achieving a profit of $13,196 versus $8,141. The strategy not only achieved higher profitability, but it did so by investing less capital overall. This means that our strategy allocated funds much more effectively by investing according to risk levels. Furthermore, by holding less of the asset during high-risk periods and more during low-risk periods, it naturally reduced drawdowns and volatility, resulting in a much higher reward per risk taken.

These results are conclusive across various combinations of strategies tested over different time frames. Anyone is free to verify this themselves using our strategy-building features. The only consideration investors need to be aware of is the total investment amount. Since future risk levels cannot be predicted with certainty, a strategy might result in slightly more or slightly less investment compared to a regular DCA approach. For example, if your average budget is $200 per month, you can use our strategy-building tools to tailor and backtest a strategy that aligns with this amount, adjusting risk levels to achieve comparable investment totals. While there may be minor deviations in the invested amount, the superior performance of our strategies remains evident. Investors with some margin of flexibility in their budgets will benefit from the clear advantages of risk-based strategies. Again, these tools are available for you to test and validate yourself using our platform.

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

Disclaimer: This section of the whitepaper was written in early 2023, meaning the simulations discussed here span two years into the future from that point.

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 general 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 Simulating Non-Price-Based Metrics

Simulating non-price-based metrics introduces additional complexity. These metrics often have intricate relationships with price movements or external variables, making straightforward modeling challenging. To address this, we rely on specific assumptions and adjustments to adapt the model for simulation purposes. This might involve omitting certain factors, manipulating parameters, or tailoring the model's structure to ensure a functional simulation. Despite these challenges, it is possible to simulate non-price-based metrics effectively by leveraging mathematical techniques such as Cholesky decomposition.

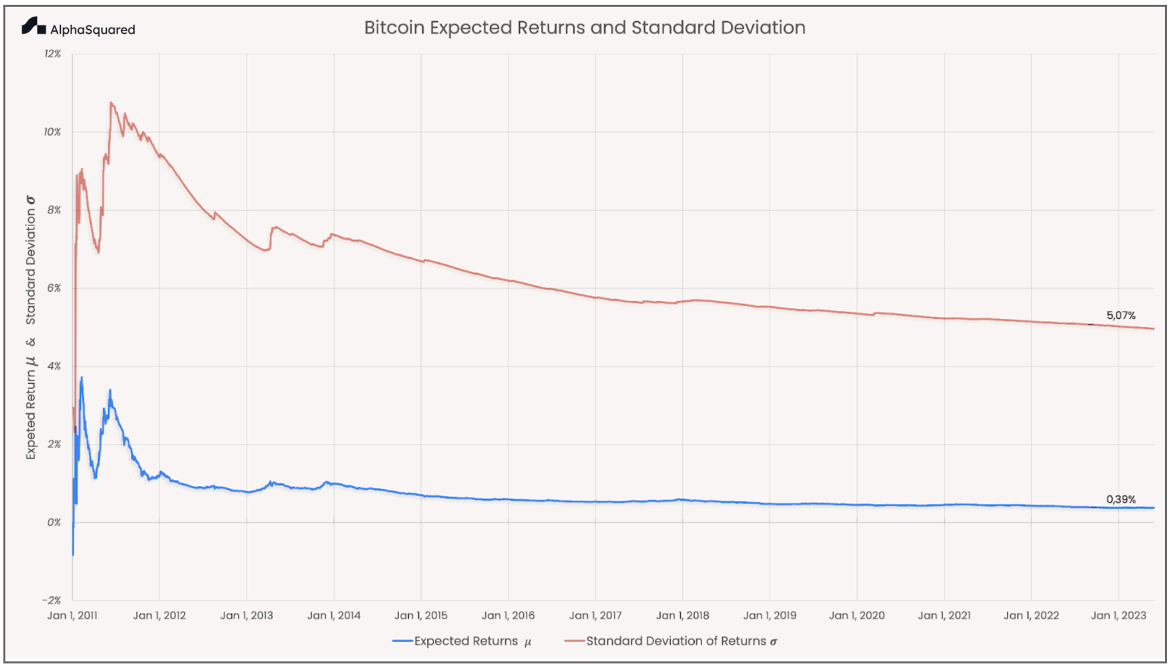
5.4.3 Cholesky Decomposition and Correlated Simulations

Cholesky decomposition is a mathematical method used to simulate correlated variables by decomposing a covariance matrix into lower and upper triangular matrices. In finance, this technique is particularly useful for modeling assets or metrics that exhibit correlation, such as trading volumes, market sentiment, or macroeconomic indicators. By applying Cholesky decomposition, we can generate correlated random variables that maintain the statistical properties observed in historical data.

For example, if we wanted to simulate both price and sentiment data while maintaining their observed correlation, Cholesky decomposition allows us to model these dependencies effectively. This approach ensures that non-price metrics align with market behavior, adding a layer of realism and robustness to our simulations

5.4.5 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, as a general rule, 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 taken into account. 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.

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.

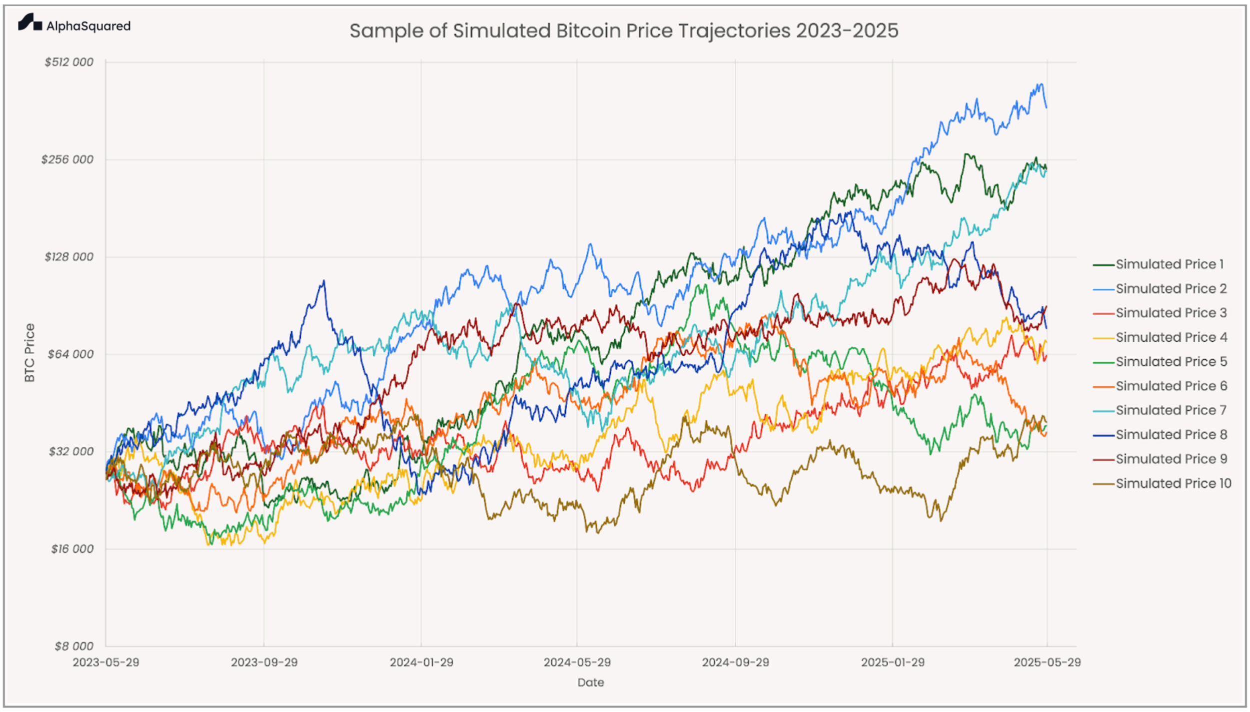
- σ is the volatility, representing the standard deviation of the returns.

- Z is a random number from a standard normal distribution (mean 0, standard deviation 1) which goes by the following formula: $f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2}$

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.



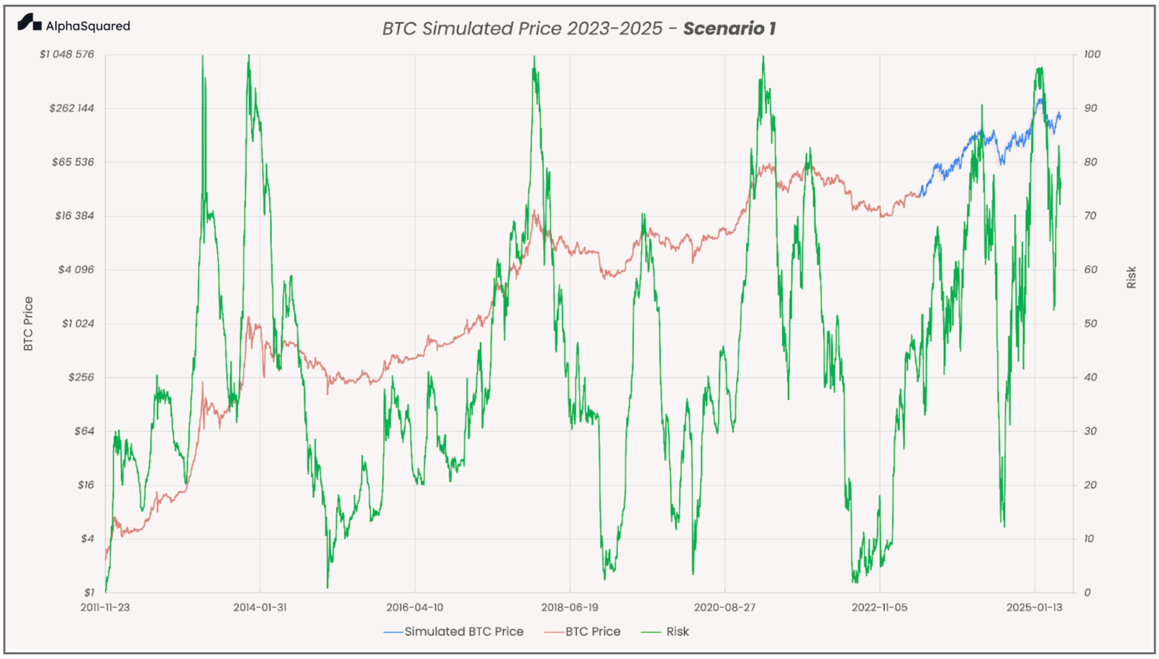
It is important to note that these trajectories are not predictions, but rather possible trajectories from a statistical standpoint. These simulations are a very close approximation to the price action of bitcoin, and they are therefore suitable to use for forward-testing our model in specific scenarios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

5.4.6 Simulation Results

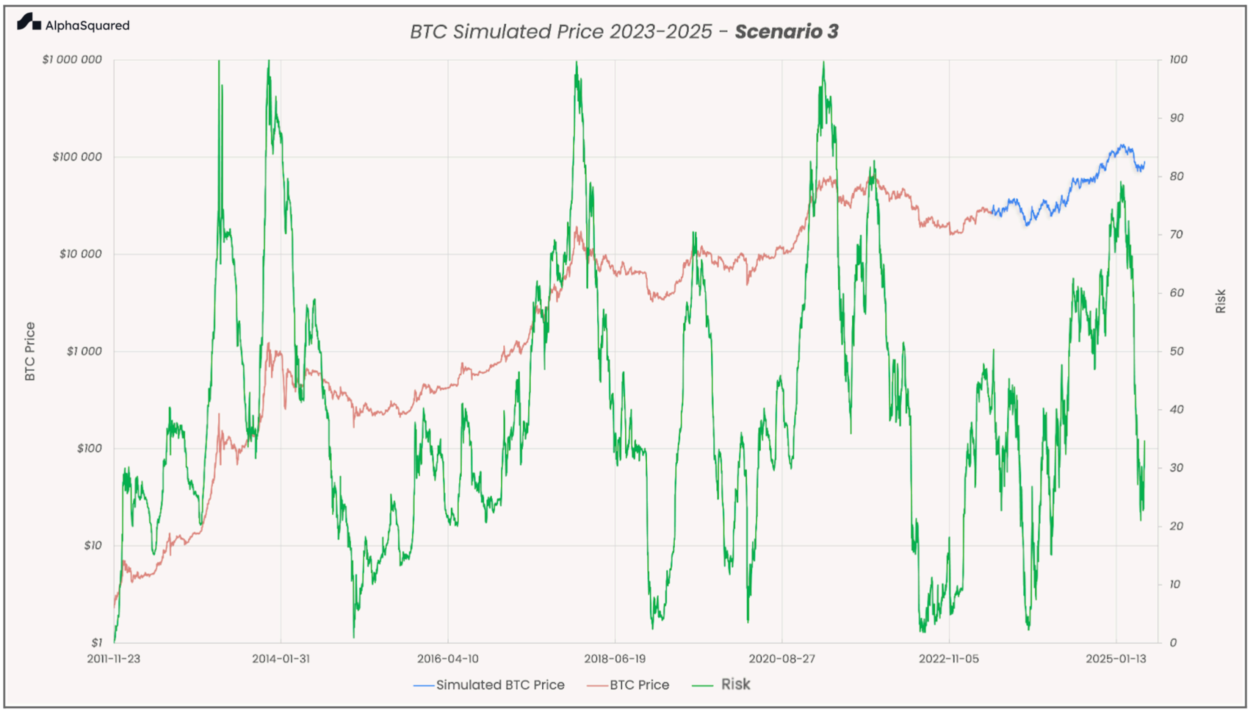


Scenario 1 displays a scenario in which Bitcoin is set to have another bull run - something in accordance with the popular “cycle theory”, reaching new all-time-highs of $328’000 by 2025.

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. Despite the fact that 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.

Conclusion of simulation 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.

5. Vision

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. 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.

With AlphaSquared, investors can expect a data-driven approach and a focus on setting realistic expectations, rather than being lured by false promises and pipe dreams. 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.

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