# RETROSPECTIVE CRITICAL ASSESSMENT OF A BITCOIN MINING PROJECT VALUATION: REALITY VS. FORECASTS FOUR YEARS LATER

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## 1. Introduction

### 1.2 Background and motivation

Bitcoin mining has evolved into a capital-intensive industry, requiring significant computational resources, high energy consumption, and strategic financial planning. The industry operates in a highly volatile environment, influenced by Bitcoin price fluctuations, technological advancements, increase in computer power deployed to the BTC-network (hashrate), and regulatory changes. Given these uncertainties, accurately valuing Bitcoin mining projects remains a challenging yet essential task for project-sponsors, investors and asset managers.

In 2020, a Bitcoin mining project, Bitcoin Minter (BMF), was proposed in the Republic of Georgia, a country known for its low electricity costs and favourable climate for mining operations. The project required an investment of c. $11.0 million and was expected to generate returns through block rewards and transaction fees. A multi-method valuation approach was employed, integrating Discounted Cash Flow (DCF) analysis, GARCH-based Monte Carlo simulations, and Real Options Pricing to assess its potential profitability. However, the project was never realized, providing an opportunity for a retrospective critical assessment of its valuation accuracy. With hindsight, this decision turned out to be the right one, as even though Bitcoin's price significantly exceeded initial forecasts, this was more than compensated by halvings of the mining rewards and growth in the BTC-mining capacity (hashrate) both making the project unprofitable had it been executed. Although the initial valuation was This study seeks to understand why the initial valuation did not justify the investment and to identify any flaws in the decision-making process.

### 1.2 Research problem and objectives

The key problem addressed in this study is to identify the reasons for the false positive outcome of the 2020 valuation. Although the valuation at the time supported a positive investment decision, the subsequent developments showed that the decision not to undertake the project was the right one.

To answer this, the study explores the following: (1) Did the valuation methods applied contain inherent flaws? (2) Were the historical analyses and data used at the time inadequate? (3) Did the assumptions made in 2020 fail to capture real-world market dynamics? (4) Were the estimations and forecasts inaccurate, and if so, why? (5) Was the methodology incorrectly applied or misinterpreted?

By addressing these questions, the study aims to reassess the valuation decision and extract insights that can improve future investment appraisals in highly uncertain environments such as cryptocurrency mining.

### 1.3 Importance of Retrospective Analysis

Unlike traditional investment projects, Bitcoin mining profitability depends on highly volatile and unpredictable factors, making ex-ante valuation inherently uncertain. This retrospective assessment provides critical insights into: (1) The effectiveness of different valuation methodologies in forecasting cryptocurrency-related investments. (2) The role of historical data analysis and assumption setting in investment decision-making. (3) The impact of Bitcoin price cycles and mining difficulty adjustments on long-term profitability. (4) The importance of applying appropriate valuation frameworks, such as GARCH-based Stochastic Processes or Real Options Pricing, to account for market uncertainties.

### 1.4 Structure of the Study

The remainder of this paper is structured as follows. Section 2 provides an extant research literature review, discussing prior studies on Bitcoin mining valuation, forecasting methodologies, and

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financial modelling techniques. This section assesses whether alternative approaches could have improved the accuracy of the original valuation. Section 3 describes the Bitcoin Minter business model, outlining its planned operations, revenue streams, and cost structure as initially conceived in 2020. Section 4 presents the 2020 valuation methods used, including discounted single point estimate expected free cash flows, stochastic modelling and simulation applying the GARCH-ARCH framework and real options lattice valuation approach. Section 5 compares actual market conditions (2021-2024) with the original forecasts. Section 6 concludes with key takeaways and strategic implications, discussing lessons learned for future investment decision-making in highly uncertain environments, such as cryptocurrency mining.

## 2. Literature Review

This section reviews existing literature on valuation methodologies and stochastic forecasting models applicable to high uncertainty investments. The focus is on assessing whether alternative approaches could have enhanced the accuracy of the 2020 valuation of the Bitcoin Minter (BMF) project. Both the 2020 valuation and this critical assessment are based on the general valuation literature that lays the foundation for corporate valuation, investment decision-making under uncertainty, and Real Options Analysis. Bitcoin mining-specific studies are examined in order provide empirical insights into mining profitability, risk factors, market cycles, and investment strategies, validating the need for flexible valuation approaches like GARCH-based Monte Carlo simulations and Real Options Pricing. Valuing Bitcoin mining ventures involves navigating significant uncertainties due to price volatility, technological advancements, and regulatory changes. Traditional valuation methods, such as Discounted Cash Flow (DCF) analysis, often fall short in capturing these dynamics. To address this, researchers have explored various models: Real Options Analysis (ROA): ROA provides a framework to value managerial flexibility in investment decisions under uncertainty. By treating investment opportunities as options, ROA accounts for the ability to defer, expand, or abandon projects in response to market developments. This approach is particularly relevant for Bitcoin mining, where market conditions are highly volatile. Stochastic Modelling Techniques: Incorporating stochastic processes into valuation allows for a more nuanced understanding of potential future states. Models such as Geometric Brownian Motion (GBM) and Mean Reversion processes have been applied to simulate Bitcoin price paths, aiding in the assessment of mining project viability. Accurate forecasting of Bitcoin's price volatility is crucial for effective risk management and valuation. Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models have been widely used in this context. GARCH Models are adequate at capturing volatility clustering in financial time series. Studies have applied GARCH models to Bitcoin, finding them effective in modelling and predicting price volatility. For instance, Naimy and Hayek (2018) demonstrated that the EGARCH(1,1) model outperformed other variants in forecasting Bitcoin's volatility. Research comparing GARCH models with other forecasting techniques, such as Exponentially Weighted Moving Average (EWMA) and machine learning approaches, indicates that while GARCH models perform well, alternative methods like Recurrent Neural Networks (RNN) can offer superior forecasting accuracy in certain scenarios. Lattice models, including binomial and trinomial trees, are instrumental in valuing options by modelling possible price paths over time. Their application extends to real options valuation in cryptocurrency investments. Binomial Lattice Models facilitate the valuation of investment opportunities by discretizing the possible future states of the underlying asset, allowing for the incorporation of managerial decision points. In the context of Bitcoin mining, binomial lattice models are used to evaluate the option to switch on/off based on future price movements. Flexibility in Decision-Making is based on integration of real options analysis with lattice models enables the valuation of managerial flexibility, a critical aspect in the volatile environment of cryptocurrency mining. This approach allows investors to make informed decisions by quantifying the value of potential strategic actions under uncertainty. The literature suggests that incorporating advanced stochastic forecasting models and real options analysis could enhance the valuation of Bitcoin mining projects. Specifically. Utilizing models that capture the unique volatility characteristics of Bitcoin, such as GARCH or machine learning-based approaches, may improve the precision of price forecasts, leading to more accurate cash flow projections. Applying real options analysis through lattice models can quantify the value of strategic decisions, such as scaling operations or delaying investments, which are pertinent in the context of Bitcoin mining. In retrospect, the application of these methodologies might have provided a more robust valuation framework for the Bitcoin Minter project, potentially leading to a different investment decision. The literature review highlights the importance of selecting appropriate valuation and forecasting models in the assessment of Bitcoin mining projects.

### 2.1. General valuation and investment under uncertainty

Copeland, Koller, & Murrin (1995) provide one of the most widely used corporate valuation frameworks, focusing on DCF, cost of capital, and risk-adjusted returns. Their methodology forms the basis for valuing Bitcoin Minter in 2020, using expected cash flows from mined Bitcoin. Dixit & Pindyck (1994) explore investment under uncertainty, highlighting the importance of option-like decision-making in volatile industries. Their insights justify the application of stochastic modeling and Real Options in Bitcoin mining, where future cash flows are uncertain. Trigeorgis (1996) sets the foundation for Real Options Analysis (ROA), demonstrating how investment decisions can incorporate flexibility under uncertainty. His work establishes theoretical basis for valuing Bitcoin mining operations as real options, where managers can expand, contract, or abandon mining operations based on market conditions. Copeland & Antikarov (2001) extend the Real Options framework, offering a practitioner's guide to applying option-based valuation methods in corporate finance. Their approach is critical for Bitcoin mining, where price volatility requires dynamic investment strategies rather than static projections. Brainard & Tobin (1968) highlight pitfalls in financial model building, an essential critique when retrospectively evaluating Bitcoin Minter's valuation errors. Their warnings about over-reliance on deterministic models reinforce the need for stochastic approaches. Velev, Dimov, & Sarastov (2019) analyze corporate capital expenditures, providing insight into investment allocation under capital constraints, which is crucial in mining, where hardware and energy costs dominate financial planning.

### 2.2. Bitcoin Mining-Specific Valuation and Risk Analysis

Berengueres (2018) presents a Net Present Value (NPV)-based valuation for crypto-mining operations, comparing holding vs. mining. He argues that mining profitability is heavily dependent on energy costs, difficulty adjustments, and Bitcoin price trends, which aligns with this study's retrospective valuation. Deng et al. (2023) discuss the risk and hedging strategies for Bitcoin mining investments, emphasizing how volatility affects long-term profitability. Their findings support the need for Monte Carlo simulations and Real Options Pricing in mining valuation. Fabus et al. (2024) examine Bitcoin's halving effects, assessing how block reward reductions impact mining sustainability and profitability. Their work is relevant for evaluating how Bitcoin Minter would have performed post-2020 halving. Zhang (2023) studies the valuation and investment risks of Bitcoin and Ethereum, providing empirical data on cryptocurrency asset pricing and risk factors that influence mining operations. Kraft (2022) investigates the business models of Bitcoin mining, specifically in Sweden. His work highlights key cost drivers, energy consumption considerations, and strategic investment decisions that parallel the Bitcoin Minter project's financial analysis.

## 3. Business Model of Bitcoin Minter (BMF)

Bitcoin Minter (BMF) aimed to establish a high-performance Bitcoin mining facility in Georgia, a country with affordable electricity and business-friendly environment for cryptocurrency operations. The project was structured as a three-year investment with the goal of maximizing returns through Bitcoin mining before a potential industry shift due to halving events and regulatory changes. The facility would consist of 14 modular mining containers, each housing high-performance mining rigs.

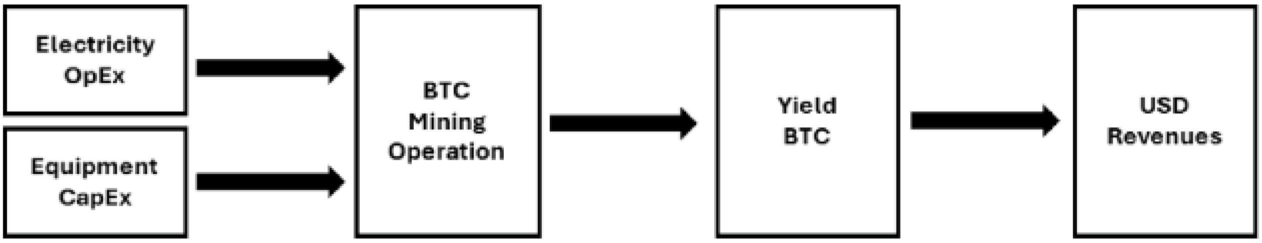



**Fig. 1. Schematic representation of the business model**

The total installed processing power of the project if executed was planned at 285,649 tera hashes per second (TH/s). This would contribute approximately 0.2842% of the total global Bitcoin mining capacity (as of early 2020 estimates). Electricity costs in Georgia were among the lowest in the world, at approximately \$0.06 per kWh. A cool climate naturally reduced cooling requirements, lowering operational expenses. The legal and tax framework in Georgia was favourable, with no direct restrictions on Bitcoin mining activities at the time. Bitcoin's block reward was 6.25 BTC per block post-May 2020 halving. Blocks were mined every 10 minutes, leading to 450 BTC mined per day globally. Given BMF's expected share of the global hashrate (0.2842%), its estimated reward was 2.56 BTC per day at the outset. In addition to block rewards, miners receive transaction fees for processing Bitcoin transactions. Historically, transaction fees contributed 5-10% of total mining revenue. For valuation purposes, transaction fees were estimated at 6% of block rewards, leading to additional daily revenue.

Bitcoin mining is a capital-intensive operation with both fixed (CAPEX) and variable (OPEX) costs. Total Initial Investment: \$10.95 million. This included BTC-mining hardware acquisition (ASIC miners, power supplies, and cooling systems), infrastructure setup (containers, transformers, and security), software & IT infrastructure for mining operations. Operating Expenses (OPEX) were estimated at \$7.17 million annually (\$19,643 per day), including electricity costs: \$0.06 per kWh totalling €6.3 million per year, maintenance and repairs ensuring mining rigs operate at optimal efficiency, personnel and security, managing daily operations and securing the facility. The competitiveness of the project heavily depended on the electricity price.

Bitcoin Minter's financial success depended on multiple external factors. Since revenue was denominated in BTC, its value in dollars fluctuated significantly. Historical Bitcoin cycles showed boom-and-bust trends affecting long-term profitability. Global Bitcoin Hashrate growth also has a tremendous impact. If global hashrate increased, BMF's share of mining rewards would decrease, reducing revenue. Mining difficulty was also expected to rise as new miners entered the network. Bitcoin's programmed halving cycle reduces block rewards every four years. The 2024 halving would lower mining rewards to 3.125 BTC per block, impacting long-term revenues. Energy cost stability is fundamental for the operating costs level. Georgia had competitive electricity rates, but global energy markets could introduce pricing risks and electricity demand from neighbouring Turkey could have increased the electricity price. Regulatory shifts in energy pricing or carbon taxation could also impact costs.

The daily revenue estimation is provided by the following:

$$E\left(R_{daily}\right) = \frac{C_{project\frac{TH}{s}}}{E(C_{global\frac{TH}{s}})} \cdot M_{BTC-daily} \cdot E\left(X_{\frac{USD}{BTC}}\right) \cdot (1 + r_t) \qquad (1)$$

where R denotes revenue, C denotes capacity, M denotes new bitcoins issuance or minting, X denotes the price of BTC in US dollars, r is the additional income of BTC transaction handling and E(.) represents the expectations operator. It is apparent that the daily project revenue is highly sensitive to Bitcoin's price, mining difficulty adjustments (halving of M), and competition in the mining network.

There are two sources of uncertainty, both denoted by the expectations operator E(.) in (1)

(1) The project's share of the bitcoins mined, M, that arises from the global capacity supplied and depends on entry and exit of competing BTC mining operators as well as the operating load of the existing BTC mining operators.

(2) The US dollar price (rate) of bitcoin, as the project gets rewarded in bitcoins, but the investment is in US dollars and the return have to be in US dollars.

A key advantage in Bitcoin mining is operational flexibility, allowing firms to adjust mining intensity based on market conditions. If Bitcoin's price fell below the breakeven level, or hash rate increase (thus reducing BMF's share of daily BTC mined) mining operations could be temporarily halted to avoid losses. The cost of maintaining idle hardware was relatively low compared to continuing unprofitable operations. If Bitcoin surged beyond expected levels, BMF could scale operations by reinvesting profits into additional mining hardware. Expansion was subject to global ASIC chip supply constraints, which could delay scaling efforts. BMF had the ability to scale up, shut down, or exit the market based on profitability forecasts. Using a binomial lattice model, the project's flexibility could be valued as a series of embedded call/put options.

The project was structured as an SPV (Special Purpose Vehicle) under a holding company. Funding was expected from a mix of equity investors seeking exposure to Bitcoin mining profits and debt financing to cover initial hardware purchases. Profits could be reinvested into mining capacity expansion. A Bitcoin treasury strategy was considered, where mined BTC would be held rather than immediately sold to capitalize on price appreciation.

| Factor | Details |
|---|---|
| Facility Size | 14 mining containers, 285,649 TH/s |
| CAPEX | €10.95 million |
| OPEX | €7.17 million per year |
| Electricity cost | ~€6.3 million per year (€0.06 per kWh) |
| Revenue | BTC block rewards + transaction fees |
| Profit drivers | BTC price, global hashrate, energy costs, BTC halving |
| Operational flexibility | Ability to shut down during losses or expand when profitable |
| Holding Strategy | Partial BTC retention for long-term price gains |

**Table 1 Project parameters**

## 4. The 2020 Valuation

This section presents the initial financial projections for the Bitcoin Minter (BMF) project as assessed in 2020. The valuation relied on a multi-method approach, integrating Discounted Cash Flow (DCF) analysis, Monte Carlo simulations (GARCH-based), and Real Options Pricing (Binomial Lattice) to estimate the project's potential Net Present Value (NPV), Internal Rate of Return (IRR), and Tobin's Q under different market conditions.

### 4.1. Economic and econometric analysis performed in 2020

Prior to determining the valuation approach and its implementation a thorough analysis on BTC, the BTC ecosystem and the key drivers of a BTC mining business was performed.

#### 4.1.1 Value drivers of the BTC mining business model

The analysis started by examining the value drivers of the project. These are presented on the following figure.

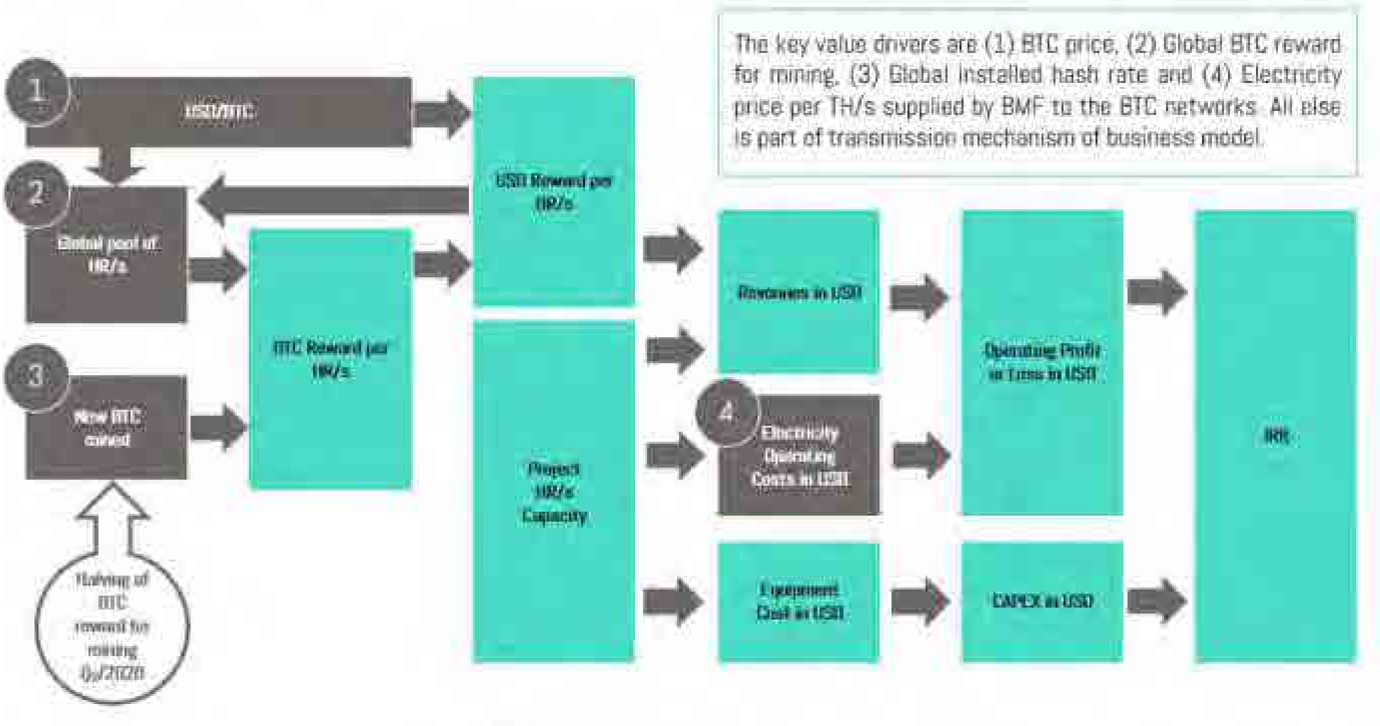



**Fig. 2. Value drivers**

Based on the analysis of the value drivers BTC price and the hash rate were singled out as the main sources of value but also sources of uncertainty. Hence a thorough econometric analysis was performed on their historical time series.

### 4.1.2 Determination of sample period

Visual examination of BTC and Hash rate time charts and descriptive statistics were performed on the time series to assess heterogeneity in their evolution.

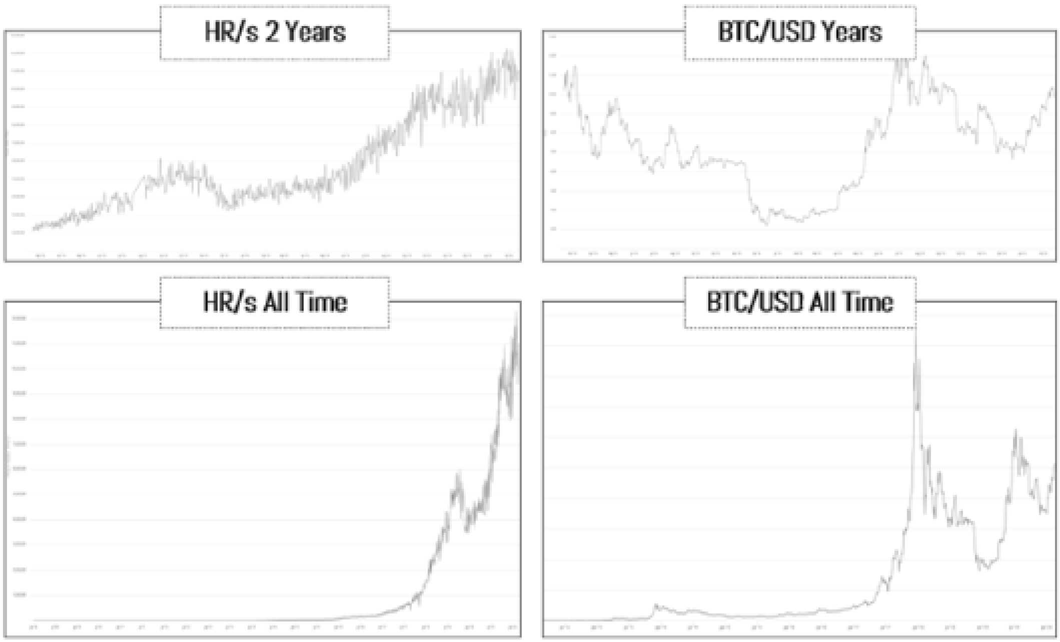



**Fig. 2. Time charts of the main sources of uncertainty**

The conclusion was that risk-return profile of BTC had evolved and changed considerably during its lifetime up to 2020. Its volatility had been very significant post inception but had receded as the asset matured towards 2020. As of 2020 the price of BTC also had shown a clear trend. Daily returns volatility was the main indicator showing the gradual taming of volatility since BTC launch in 2010. The BTC returns had tended towards becoming stationary. Distribution of returns had been however far from normal with very high kurtosis.

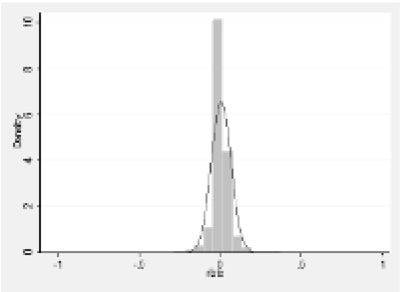


**Fig. 2 Distribution of BTC returns**

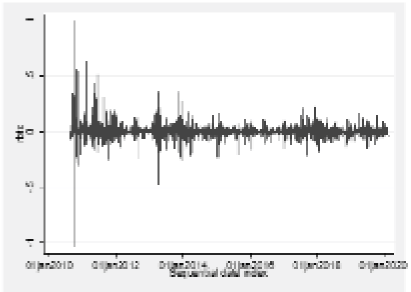


**Fig.3 Daily BTC returns**

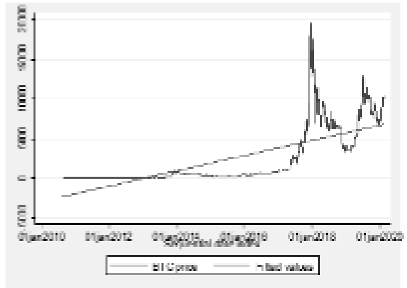


**Fig.4 BTC price and trend**

Based on the initial visual examination a two-year estimation period was selected at the time to outline the statistical properties of both the BTC and the Hash rate. The sampling period and its proportion to the whole population are presented in the following figure.

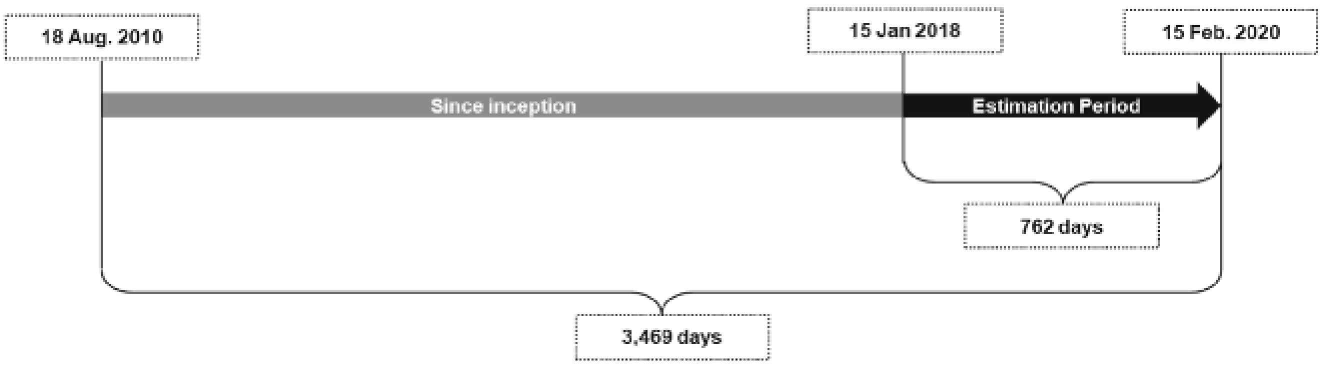



**Fig.5 Estimation sample period and the whole population since BTC inceptions**

**4.1.3 Statistical properties of BTC over the same period**

The forecasting of the evolution of the BTC price and returns was justifiably based on historical analysis of BTC over the same period.

rbtc

| | Percentiles | Smallest | | |
|---|---|---|---|---|
| 1% | -.1124027 | -.1845817 | | |
| 5% | -.0644871 | -.1739821 | | |
| 10% | -.0450053 | -.1510193 | Obs | 700 |
| 25% | -.0167403 | -.1435615 | Sum of Wgt. | 700 |
| 50% | .0010141 | | Mean | -.0009855 |
| | | Largest | Std. Dev. | .0390072 |
| 75% | .015548 | .1217555 | | |
| 90% | .0388258 | .1241269 | Variance | .0015216 |
| 95% | .0623323 | .1447609 | Skewness | -.2021145 |
| 99% | .1084668 | .1600431 | Kurtosis | 6.208517 |

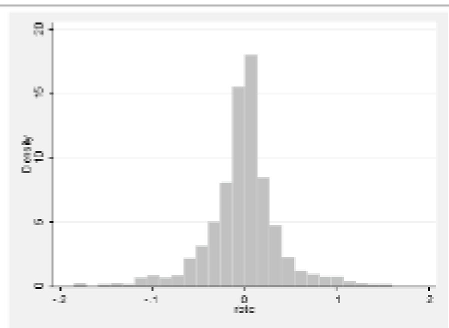


**Fig.6 Statistical properties of BTC price daily returns over the sample period**

BTC Price

| | Percentiles | Smallest | | |
|---|---|---|---|---|
| 1% | 3424.59 | 3236.76 | | |
| 5% | 3630.68 | 3242.48 | | |
| 10% | 3857.72 | 3252.84 | Obs | 701 |
| 25% | 5903.44 | 3313.68 | Sum of Wgt. | 701 |
| 50% | 7354.13 | | Mean | 7337.05 |
| | | Largest | Std. Dev. | 2356.75 |
| 75% | 8987.05 | 12573.81 | | |
| 90% | 10518.17 | 12899.2 | Variance | 5554270 |
| 95% | 11225.3 | 13016.23 | Skewness | .0396065 |
| 99% | 11966.41 | 13819.8 | Kurtosis | 2.220771 |

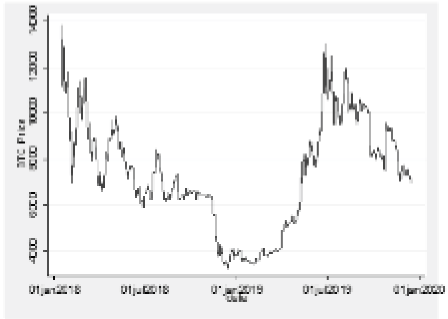



**Fig.7 Statistical properties of BTC price over the estimation period**

### 4.1.4 Halving and the Stock-to-Flow model

Halving is a major event in BTC price dynamics and the revenue arising from mining BTC, as it decreases by 50% the BTC minted per block provided to whole mining community as a reward for maintaining the distributed ledger technology underpinning the BTC ecosystem. Therefore, the market effects of the first halving in 2012 and the second in 2016 were examined.

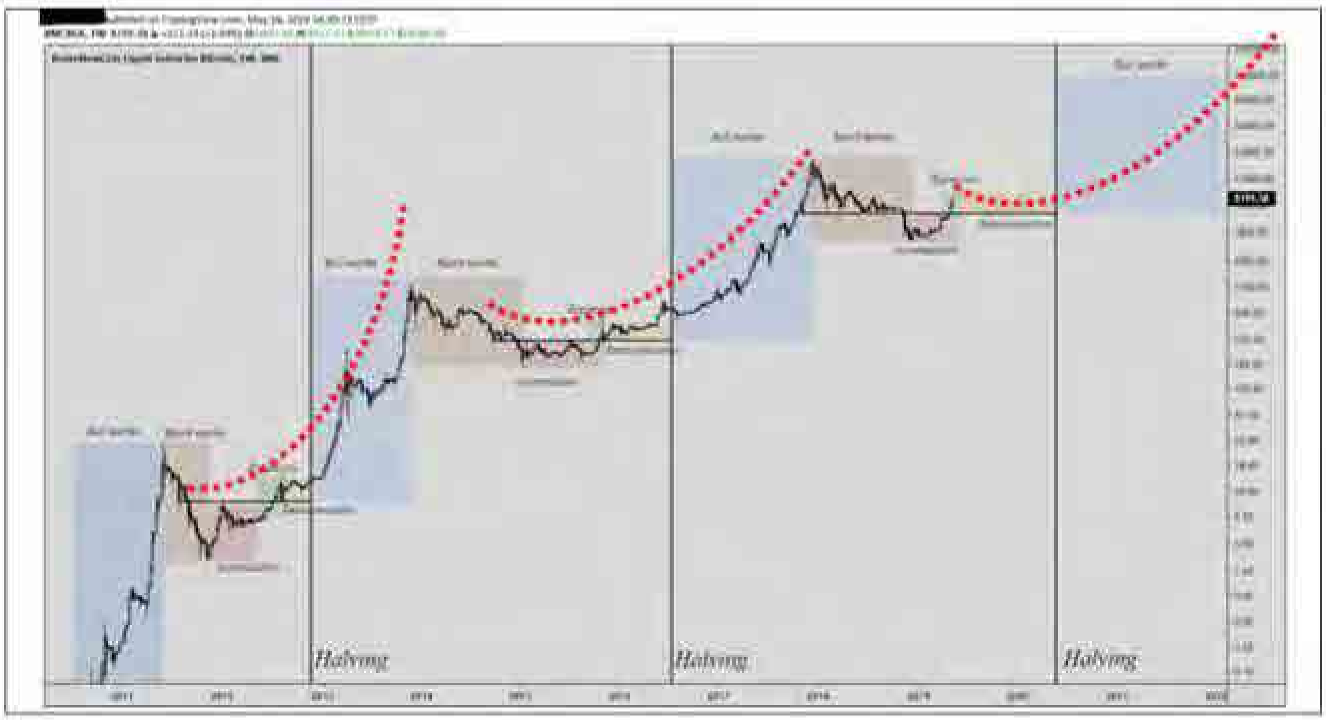



**Fig.8 Effects of third halving in 2020 at inception of BMF project**

A stock to new issue supply-side model, named Stock-to-Flow was tested on the series. The Stock-to-Flow model is a widely used framework for predicting Bitcoin's future price based on its scarcity. The model was popularized by the anonymous analyst PlanB (2019) and is inspired by commodity pricing models for gold and silver.

$$STF\ coefficient = \frac{Stock}{Annual\ New\ Supply} \qquad (2)$$

Where stock is the total existing Bitcoin (BTC) in circulation. Flow is the number of new BTC mined each year. A higher STF ratio indicates higher scarcity, leading to a higher expected price. As BTC supply decreases over time due to halvings (every 4 years), its STF ratio increases. This increased scarcity historically correlates with higher BTC prices.

| Halving Cycle | Total BTC in circulation (Stock) | Annual new BTC Issue (Flow) | Stock-to-Flow Ratio (STF) | Historical BTC Price |
|---|---|---|---|---|
| Pre-2012 Halving | 10.5M BTC | 3.6M BTC/year | 2.9 | ~$5 |
| 2012-2016 | 15.75M BTC | 1.8M BTC/year | 8.75 | ~$650 |
| 2016-2020 | 18.375M BTC | 0.9M BTC/year | 20.4 | ~$9,000 |
| 2020-2024 | 19.687M BTC | 0.45M BTC/year | 43.7 | ~$60,000 |
| 2024-2028 (Projected) | 20.343M BTC | 0.225M BTC/year | 90.4 | $100K+ (Model Prediction) |

**Table 2 Stock to Flow Statistics**

The STF model developer proposed a logarithmic regression model linking S2F to BTC price:

$$ln(X) = a + b.ln(STF) \qquad (3)$$

Where, a, and b are regression coefficients derived from past data and STF is the stock of BTC to new issuance (Flow).

Hence:

$$X = e^{a+b.ln\,(STF)} \qquad (4)$$

The model is aligned well with BTC price trends. Scarcity-based models perform well for commodities (gold, silver). However, the model ignores demand-side factors (adoption, regulation, macroeconomics). The model is overly deterministic as BTC price is more volatile than STF predicts. In 2022 the model failed to predict accurately the BTC bear market as the BTC price fell below the model predictions. The model has to be further extended to include demand and may incorporate network adoption metrics and macro analysis to include factor in the impact of interest rates, liquidity cycles, and institutional flows.


**Fig.9 Effects of third halving in 2020 at inception of BMF project**

The results of the regression analysis performed on the natural logarithm of BTC prices against the natural logarithm of STF ratio are presented on Fig.10. Estimated $R^2$ is high and hence indicates likely significance. Regression does not prove causality. Economically meaningful influence is drop in supply. Many other factors are at play in forming BTC price.

| Source | SS | df | MS | | |
|---|---|---|---|---|---|
| Model | 27474.5664 | 1 | 27474.5664 | Number of obs = | 3408 |
| Residual | 3495.18788 | 3406 | 1.02618552 | F( 1, 3406) = | 26773.45 |
| Total | 30969.7543 | 3407 | 9.09003648 | Prob > F = | 0.0000 |
| | | | | R-squared = | 0.8871 |
| | | | | Adj R-squared = | 0.8871 |
| | | | | Root MSE = | 1.013 |

| lprice | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| s2f | 3.062334 | .0187154 | 163.63 | 0.000 | 3.025639 | 3.099028 |
| _cons | -19.55032 | .1535943 | -127.29 | 0.000 | -19.85147 | -19.24917 |

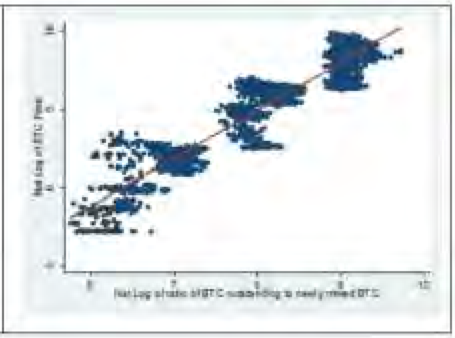


**Fig. 10 Descriptive power of STF model.**

Estimated $R^2$ is high and hence indicates likely significance. Regression does not prove causality. Economically meaningful influence is drop in supply. Many other factors are at play in forming BTC price.

### 4.1.5 Properties of the Hash rate

An examination of the statistical properties of Hash rate since inception of BTC was conducted in 2020 in order to properly define and specify a forecasting model. The results are presented in Fig 11 and 12. The Hash rate is tightly correlated to BTC price.

Hash Installed

| | Percentiles | Smallest | | |
|---|---|---|---|---|
| 1% | .0079317 | .0033327 | | |
| 5% | .1914922 | .0033836 | | |
| 10% | 8.076296 | .0035617 | Obs | 3409 |
| 25% | 23.76016 | .0042485 | Sum of Wgt. | 3409 |
| 50% | 343810.3 | | Mean | 1.15e+07 |
| | | Largest | Std. Dev. | 2.26e+07 |
| 75% | 6578538 | 1.08e+08 | | |
| 90% | 4.68e+07 | 1.09e+08 | Variance | 5.11e+14 |
| 95% | 6.03e+07 | 1.12e+08 | Skewness | 2.195571 |
| 99% | 9.48e+07 | 1.14e+08 | Kurtosis | 7.174134 |

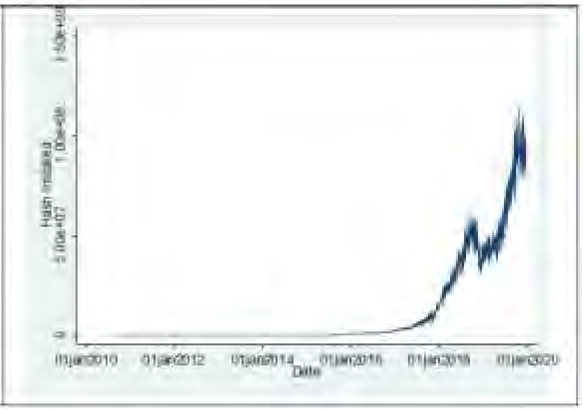



**Fig.11 Statistical properties of installed Hash Power over the estimation period**

Hashrate

| | Percentiles | Smallest | | |
|---|---|---|---|---|
| 1% | 1.83e+07 | 1.51e+07 | | |
| 5% | 2.29e+07 | 1.51e+07 | | |
| 10% | 2.56e+07 | 1.51e+07 | Obs | 701 |
| 25% | 3.61e+07 | 1.65e+07 | Sum of Wgt. | 701 |
| 50% | 4.65e+07 | | Mean | 5.12e+07 |
| | | Largest | Std. Dev. | 2.20e+07 |
| 75% | 5.82e+07 | 1.08e+08 | | |
| 90% | 8.85e+07 | 1.14e+08 | Variance | 4.86e+14 |
| 95% | 9.48e+07 | 1.14e+08 | Skewness | .0392405 |
| 99% | 1.05e+08 | 1.14e+08 | Kurtosis | 2.99639 |

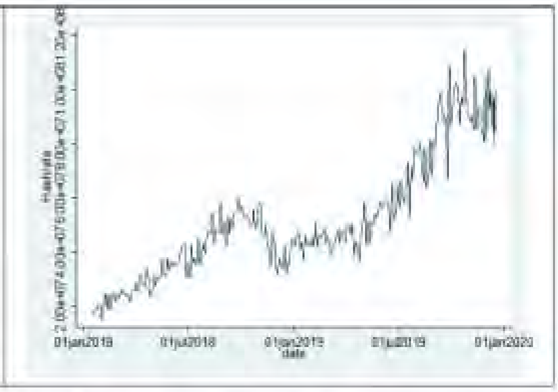



**Fig.12 Statistical properties of Hash Rate over the estimation period**

General consensus at the time of the 2020 valuation was that the Bitcoin halving would reduce miners' profitability at least for the short term. All that depended on the price of BTC after the halving. Mining was already competitive and resource-extensive and coupled with the impending block reward reduction, inefficient players would find that revenue is insufficient to pay for the costs of running their rigs. The hash rate may be affected if fewer miners contribute to the network, this will likely only be short term. If the reward halves, the hash rate is likely to drop off. However, because there is less supply being created over time, the halving may cause the price of Bitcoin to rise, thereby increasing the value of the now smaller reward. This means that in the long run, the halving will probably not have a major impact on hash rate. Although the hash rate may decrease in the short term, it is unlikely that hash rates will drastically decrease.

#### 4.1.6 Unit Mining Revenues

$$E(UMR_{daily}) = \frac{1}{E(C_{global\frac{TH}{s}})} \cdot M_{BTC-daily} \cdot E\left(X_{\frac{USD}{BTC}}\right) \cdot (1 + r_t) \qquad (5)$$

Unit Mining Revenue - USD/TH/s per day

| | Percentiles | Smallest | | |
|---|---|---|---|---|
| 1% | .1391305 | .1300292 | | |
| 5% | .1447975 | .1343055 | | |
| 10% | .1511434 | .1354817 | Obs | 762 |
| 25% | .166843 | .1358128 | Sum of Wgt. | 762 |
| 50% | .2329234 | | Mean | .322841 |
| | | Largest | Std. Dev. | .2519425 |
| 75% | .3435242 | 1.69548 | | |
| 90% | .6116663 | 1.708835 | Variance | .063475 |
| 95% | .9629261 | 1.780047 | Skewness | 2.845751 |
| 99% | 1.462527 | 1.988847 | Kurtosis | 13.29189 |

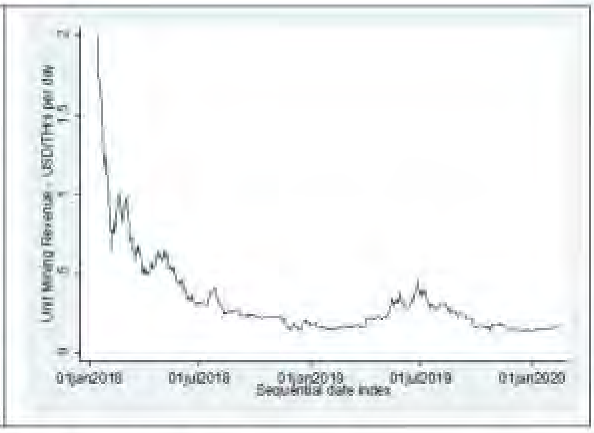



**Fig.13 Unit Mining Revenue over the estimation period**

BTC/USD affects the supply of hashrate. BTC/USD directly affects the dollar denominated UMR. Hashrate affects UMR as it is the divisor to arrive from rewards to UMR. UMR seems to be hitting a floor which is formed by hashrate coming in and going out as some miners hit marginal costs exceeding marginal revenue.

#### 4.1.7 The Relation between BTC and Hash rate

| Source | SS | df | MS |
|---|---|---|---|
| Model | 28762.0486 | 1 | 28762.0486 |
| Residual | 2271.46413 | 3407 | .666705058 |
| Total | 31033.5127 | 3408 | 9.10607768 |

| | |
|---|---|
| Number of obs | = 3409 |
| F( 1, 3407) | =43140.59 |
| Prob > F | = 0.0000 |
| R-squared | = 0.9268 |
| Adj R-squared | = 0.9268 |
| Root MSE | = .81652 |

| lprice | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. Interval] | |
|---|---|---|---|---|---|---|
| lhash | .4411675 | .002124 | 207.70 | 0.000 | .437003 | .445332 |
| _cons | .8535807 | .02605 | 32.77 | 0.000 | .8025055 | .9046559 |

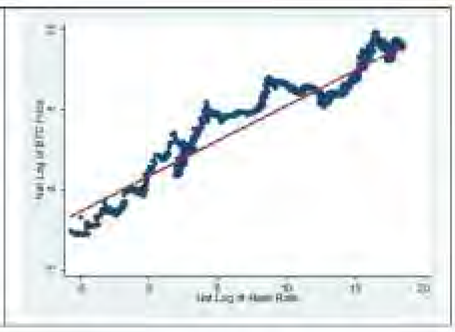


**Fig.14 Strength of the relation**

### 4.1.8. GARCH analysis of BTC and Hash rate

Several differently specified trials of GARCH-ARMA approaches were performed in the 2020 attempt to parametrise the subsequent simulation of BTC price evolution. The best performing model identified was a GARCH(1,1), ARMA (1,1) process. The sample period was the estimation period as previously defined. The Wald test ($\chi^2$ = 115.86, p = 0.0000) indicated high significance thus rejecting the null hypothesis that coefficients are jointly zero. The BTC returns mean estimation equation of the ARMA(1,1) process is:

$$r_t = \mu + \varphi_1 r_{t-1} + \theta_1 \epsilon_{t-1} + \epsilon_t \qquad (6)$$

The results are presented in the following table.

| Coefficient | Estimate | Std. Error | z-Value | p-Value | 95% Confidence Interval |
|---|---|---|---|---|---|
| Intercept (μ) | -0.00355 | 0.00636 | -0.56 | 0.577 | [-0.0160, 0.0089] |
| AR(1) ($\varphi_1$) | 0.18490 | 0.10038 | 1.84 | 0.065 | [-0.0118, 0.3816] |
| MA(1) ($\theta_1$) | 0.64848 | 0.08989 | 7.21 | 0.000 | [0.4723, 0.8247] |

**Table 3 : ARMA (1,1) for BTC Returns**

Intercept ($\mu$) is not significant ($p$=0.577, meaning the BTC returns do not have a strong drift over this period. AR(1) ($\phi_1$ = 0.1849, p = 0.065) suggests some weak autocorrelation in BTC returns. However, it's only marginally significant. MA(1) ($\theta_1$ = 0.6485, p = 0.000) is highly significant, indicating that past shocks (innovations) strongly impact current returns. This suggests BTC returns exhibit momentum and mean-reversion behaviour.

The variance estimation equation of the GARCH (1,1) process estimated is:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (7)$$

| Coefficient | Estimate | Std. Error | z-Value | p-Value | 95% Confidence Interval |
|---|---|---|---|---|---|
| ARCH(1) ($\alpha_1$) | 0.1035 | 0.0661 | 1.56 | 0.118 | [-0.0261, 0.2331] |
| GARCH(1) ($\beta_1$) | 0.7850 | 0.1233 | 6.37 | 0.000 | [0.5434, 1.0266] |
| Variance Constant ($\alpha_0$) | 0.000195 | 0.000146 | 1.34 | 0.181 | [-0.00009, 0.00048] |

**Table 4: GARCH (1,1) for BTC Returns**

ARCH(1) ($\alpha_1$ = 0.1035, p = 0.118) is not statistically significant, meaning past squared shocks (volatility clustering) are not strongly influencing future volatility. The GARCH(1) ($\beta_1$ = 0.7850, p = 0.000) is highly significant, suggesting that volatility is highly persistent pointing to long memory. The constant ($\alpha_0$ = 0.000195, p = 0.181) is not significant, meaning unconditional variance is not strongly different from zero. The results suggest that BTC returns are strongly influenced by past shocks (MA(1) = 0.6485, p = 0.000). The weak auto-correlation (AR(1) = 0.1849, p = 0.065) indicate some momentum in BTC price changes. The GARCH(1) term ($\beta_1$ = 0.7850, p = 0.000) is very strong, indicating that BTC volatility is persistent. ARCH(1) term ($\alpha_1$ = 0.1035, p = 0.118) is weak, suggesting that short-term shocks do not strongly drive future volatility.

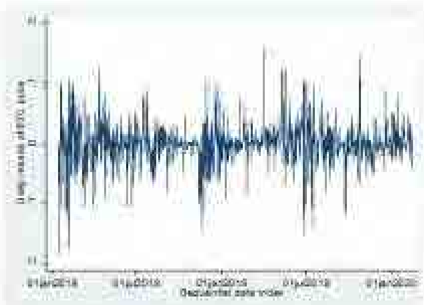


Fig. 15 Daily returns of BTC

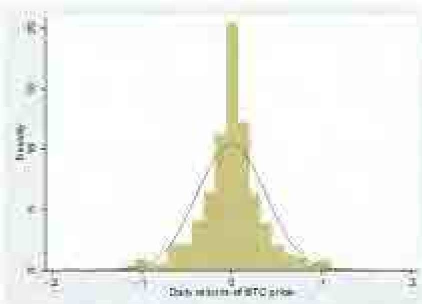


Fig. 16 BTC returns distribution

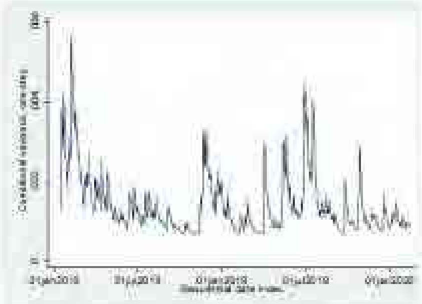


Fig. 17 Conditional Variance

It was made apparent from fig. 15 that there was clustering of volatility that had to be taken into account in the stochastic simulation of future returns. The return were symmetric. The conditional volatility from the estimation but also apparent on fig. 17 showed clustering with well defined spikes. Altogether, the series are characterised by random rapid changes and are volatile. The volatility seems to change significantly over time. The series are leptokurtic. Despite bursts and clustering volatility is tamed within certain bounds. Therefore, GARCH seems to be a suitable model for describing and driving BTC forward. However, it does not resolve the question about direction and drift of BTC/USD. Certain adjustments would have to be made to use estimated parameters for forecasting. Variance was to be targeted at estimated expected levels rather than simply fed back into a a simulation model.

Since the hash rate is considered dependent on BTC the necessary changes were introduces in the returns estimation equation for the hash rate.

$$r_t = \beta_0 + \beta_1 r_{BTC,t-1} + \phi_1 r_{t-1} + \theta_1 \epsilon_{t-1} + \epsilon_t \quad (8)$$

The results are presented in the following table:

| Coefficient | Estimate | Std. Error | z-Value | p-Value | 95% Confidence Interval |
|---|---|---|---|---|---|
| **ARCH(1) ($\alpha_1$)** | 0.1035 | 0.0661 | 1.56 | 0.118 | [-0.0261, 0.2331] |
| **GARCH(1) ($\beta_1$)** | 0.7850 | 0.1233 | 6.37 | 0.000 | [0.5434, 1.0266] |
| **Variance Constant ($\alpha_0$)** | 0.000195 | 0.000146 | 1.34 | 0.181 | [-0.00009, 0.00048] |

**Table 5: ARMA (1,1) Results for Hash Rate Returns**

Intercept ($\beta_0 = 0.0104$, $p = 0.001$) is statistically significant and positive, meaning hash rate exhibits a steady growth trend. This is consistent with Bitcoin network growth over time. BTC Returns ($\beta_1 = 0.0328$, $p = 0.501$) is not statistically significant ($p > 0.05$), suggesting no strong evidence that BTC price returns directly drive hash rate returns. This however indicates a lagged or nonlinear relationship that requires further testing. AR(1) ($\phi_1 = -0.5950$, $p = 0.123$) is not statistically significant, meaning past hash rate returns do not significantly predict current returns. MA(1) ($\theta_1 = 0.7014$, $p = 0.040$) is statistically significant, meaning past shocks (innovations) strongly impact current hash rate returns. It also suggests momentum and mean-reverting behaviour in hash rate volatility. The analysis performed indicated that a stochastic process based on GARCH(1,1)-ARMA(1,1) with integration of correlation between BTC and Hash may be used to perform a Monte Carlo simulation of the evolution of the BTC and Hash.

**4.2 Valuation methods applied in the 2020 valuation**

Bitcoin Minter's financial valuation in 2020 was based on three key methodologies: (1) Discounted single point estimate expected cash flows, (2) Monte Carlo Simulation based on GARCH approach and (3) Real Options approach to account for the flexibility of the project.

#### 4.2.1 Discounted Cash Flow (DCF) Analysis

The DCF method was used to estimate the intrinsic value of the project by discounting a single point estimate expected future cash flows at an appropriate risk-adjusted rate. The Projected Bitcoin earnings were derived from BMF's estimated 2.56 BTC/day mining output. Bitcoin price growth scenario was modelled using historical BTC price trends and consensus forecasts. In particular the single point estimate was based on the STF model already described. Electricity and operational costs were considered stable.

A standard approach was applied to estimate the present value of the expected future cash flows form the project.

$$NPV \; = \sum_{i=1}^{n} \frac{F_i}{(1+r_i)^i} - I_0 \quad (9)$$

Where F denotes the free cash flows, r - the discount rate, I - the initial investment and t - the time to horizon, t=1,2,3 after which point in time the equipment was expected to become obsolete.

The forecast income statement and cash flow statement are presented in fig. (18) and fig. (19). Estimation of the cost of capital was performed by regressing the BTC returns on the S&P500 returns for the estimation period. The results are presented in the following figure and Beta coefficient is estimated at 0.53, which at the time was considered appropriate as the BTC market was very weakly correlated with the US stock market.

| [illegible] | [illegible] | [illegible] | [illegible] |
|---|---|---|---|
| **Revenues** | **16,162,675** | **16,991,353** | **17,862,518** |
| **Costs:** | | | |
| Electriciy costs of BTC mined (COGS) | -6,571,714 | -6,571,714 | -6,571,714 |
| Monitoring, maintenance and support costs | -473,473 | -473,473 | -473,473 |
| Staff costs | -122,400 | -122,400 | -122,400 |
| **Total operating costs** | **-7,167,587** | **-7,167,587** | **-7,167,587** |
| **EBITDA** | **8,995,088** | **9,823,766** | **10,694,931** |
| Depreciation | -3,649,691 | -3,649,691 | -3,649,691 |
| **Operating profit** | **5,345,397** | **6,174,075** | **7,045,240** |
| Corporate Tax on Profit | -534,540 | -617,407 | -704,524 |
| **Net profit to shareholders** | **4,810,857** | **5,556,667** | **6,340,716** |

**Fig. 18 Forecast Income Statement**

| | | | | | |
|---|---|---|---|---|---|
| Operating profit (EBIT) | | | 5,345,397 | 6,174,075 | 7,045,240 |
| Income from associated entities | | | - | - | - |
| Increase / (decrease) of provisions | | | - | - | - |
| Corporate tax on operating profit | | | - | - 534,540 | - 617,407 |
| **NOPLAT** | | | **5,345,397** | **5,639,535** | **6,427,832** |
| | | | | | |
| Expending of provisions | | | - | - | - |
| Depreciation | | | 3,649,691.19 | 3,649,691.19 | 3,649,691.19 |
| **Gross cash flow** | | | **8,995,087.71** | **9,289,226.12** | **10,077,523.60** |
| | | | | | |
| CAPEX | | | - | - | - |
| Change in working capital | | | 49,731 | 2,550 | 2,681 |
| **Gross investments** | | | **49,731** | **2,550** | **2,681** |
| | | | | | |
| **Free cash flow** | **65.78%** | **- 11,049,074** | **9,044,819** | **9,291,776** | **10,080,204** |
| Raising / (pay-back) of equity capital | | | - | - | - |
| Raising / (repayment) of short-term debt | | | - | - | - |
| Raising / (repayment) of long-term debt | | | - | - | |
| Interest income | | | - | - | - |
| Interest expenses | | | - | - | - |
| Dividends | | | - 4,810,857 | - 5,556,667 | - 6,340,716 |
| **Net change in cash** | | | **4,233,962** | **3,735,109** | **3,739,488** |

**Fig. 19 Forecast Cash Flow Statement**

| Source | SS | df | MS |
|---|---|---|---|
| Model | .027827289 | 1 | .027827289 |
| Residual | 2.84048966 | 258 | .01100965 |
| Total | 2.86831695 | 259 | .011074583 |

| | |
|---|---|
| Number of obs | = 260 |
| F( 1, 258) | = 2.53 |
| Prob > F | = 0.1131 |
| R-squared | = 0.0097 |
| Adj R-squared | = 0.0059 |
| Root MSE | = .10493 |

| rbtc | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| rsp | .5331403 | .3353457 | 1.59 | 0.113 | -.127223 | 1.193504 |
| _cons | .0125221 | .0065234 | 1.92 | 0.056 | -.0003238 | .0253679 |

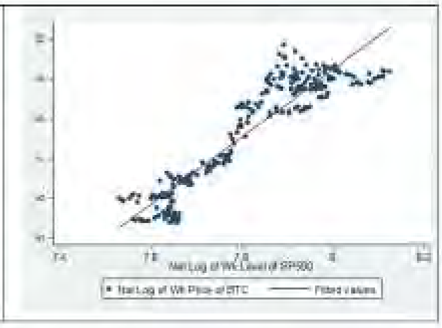


**Fig. 20 Estimation of the Beta coefficient**

In estimating the cost of capital several considerations were taken into account. The project had no debt leverage. Hence the opportunity cost of capital (WACC) equals the cost of equity capital. Country risk premium for the Republic of Georgia had to be applied. BTC beta was estimated at 0.53, but when related to cost of electricity the project beta had to be adjusted to 1.00. Risk free rate in 2020 was assumed to be 1 % and MRP was assumed to be 6% based on a consensus average among several reputable sources resulting in opportunity cost of capital at 7%. Adding a country risk premium for Georgia at 3%, again a market consensus figure, made the rate applied in the 2020 valuation equal 10%.

Univariate sensitivity analysis was performed different levels of USD revenue per TH per day which captures the joint effect of BTC price and Hash.


**Fig. 21 Breakeven analysis on USD revenue per unit capacity**

### 4.2.2 Monte Carlo Simulation (ARMA-GARCH-Based)

To model Bitcoin's high volatility, the DCF analysis was complemented with a GARCH-based Monte Carlo simulation. This approach simulated 1000 possible Bitcoin price paths, incorporating: (1) Mean-reverting properties (Bitcoin price fluctuations are not purely random), (2) Volatility clustering (large price movements tend to be followed by further volatility). (3) Historical BTC price behaviour to improve future predictions. (4) Monte Carlo outputs provided a distribution of NPVs, helping identify expected returns, best-case, and worst-case scenarios. The applied model consisted of the following main components:

a) Mean Equation - ARMA Process for BTC Returns:

$$r_t = \mu + \phi r_{t-1} + \theta \epsilon_{t-1} + \epsilon_t \quad (10)$$

Where: $r_t$ are the returns of BTC at time $t$, $\mu$ is the estimated mean return, $\phi$ is the estimated AR(1) coefficient, factoring in the autocorrelation of returns and $\theta$ is the estimated coefficient capturing past shock effects, $\epsilon$ is the error term or the innovation at time $t$.

b) Variance Equation GARCH (1,1) for Volatility Modelling

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (11)$$

Where: $\sigma_t^2$ is the conditional variance (volatility) at time $t$, $\alpha_0$ is the estimated unconditional persistent variance, $\alpha_1$ is the estimated ARCH coefficient capturing the impact of past innovations to represent the clustering of volatility, $\beta_1$ is the GARCH term, representing the persistence of volatility over time, $\epsilon_{t-1}^2$ is the lagged error term representing innovation over the previous period.

c) Generation of random returns for BTC

$$\epsilon_t = \sigma_t Z_t, \quad Z_t \sim N(0,1) \quad (12)$$

Where $\epsilon_t$ is the stochastic return shock for time $t$, $\sigma_t$ is the estimated volatility from (11) and Z is a random standard normal variable.

d) Conversion of simulated returns to BTC Price

$$P_t = P_{t-1} \times e^{r_t} \quad (13)$$

Since the revenues of the project also depended on the hash rate evolution and its uncertainty the process for modelled in a similar fashion but also made partially dependent on the BTC returns process through the following:

$$r_t = \mu + \gamma r_{btc,t-1} + \phi r_{t-1} + \theta\epsilon_{t-1} + \epsilon_t \quad (14)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\epsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \quad (15)$$

Where all parameters and terms are as described above, but relate to the hash process, except for γ coefficient representing the influence of BTC returns and $r_{btc,t-1}$ denoting the lagged return of BTC from the parallel BTC returns process.

Since hash rate follows an exponential process, the actual hash rate at time *t* is:

$$H_t = H_{t-1}e^{r_t} \quad (16)$$

Where $r_t$ is the return of hash from (14).

As a result, BTC price returns follow ARMA-GARCH process. Hash rate returns are also modelled with ARMA-GARCH process but also depend on BTC returns via the coefficient γ. BTC and Hash Rate evolve exponentially, based on their respective returns.

The generated values are used to calculate revenues from (1) for each day. The Monte Carlo approach is graphically represented in the following figure.

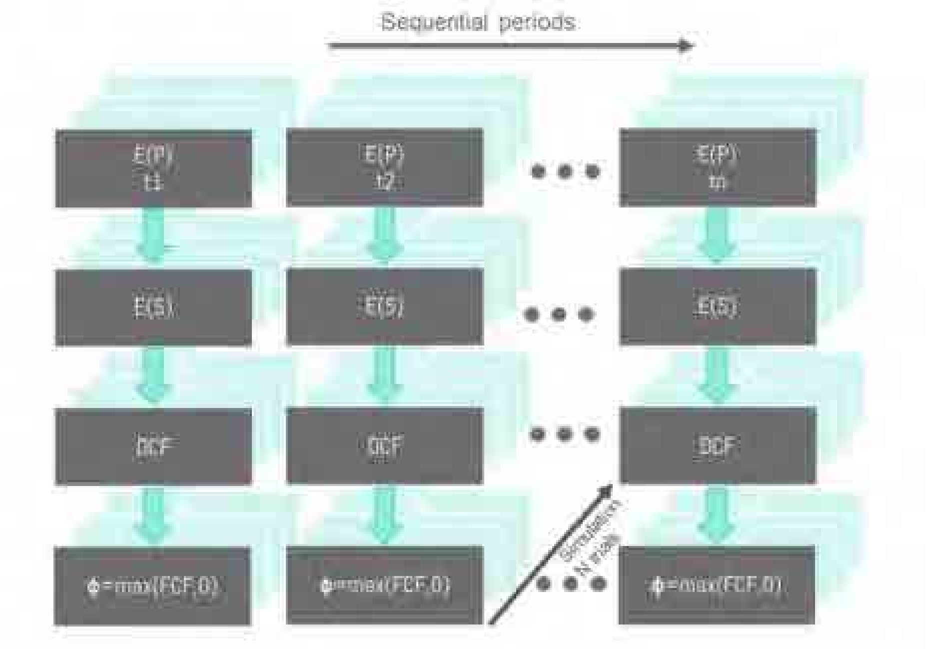



**Fig. 22 Monte Carlo Simulation (ARMA-GARCH-Based)**

In essence the estimated revenues are used to calculate the FCF using the single point DCF model, already, specified as a transfer function. The flexibility, to operate or not on a given day could be factored in even at that stage.

### 4.2.3 Real Options Pricing (Binomial Lattice Model)

Given the uncertainty in Bitcoin mining, a Binomial Lattice Model was applied to capture managerial flexibility in decision-making. The real options considered were the sequential options to operate or not on a given day given the combination of BTC price and global Hash rate, ($BTC_t$, Hash Rate). Options to expand capacity were not considered as sponsors of the project excluded subsequent commitments to further investments. Options to Contract 9scale down) if BTC mining became unprofitable were not considered, either as second market for the equipment was considered negligible.

The binomial tree approach assessed the project as a series of embedded options, refining the valuation beyond the traditional DCF methods.

The approach is graphically represented on the Fig. 23.

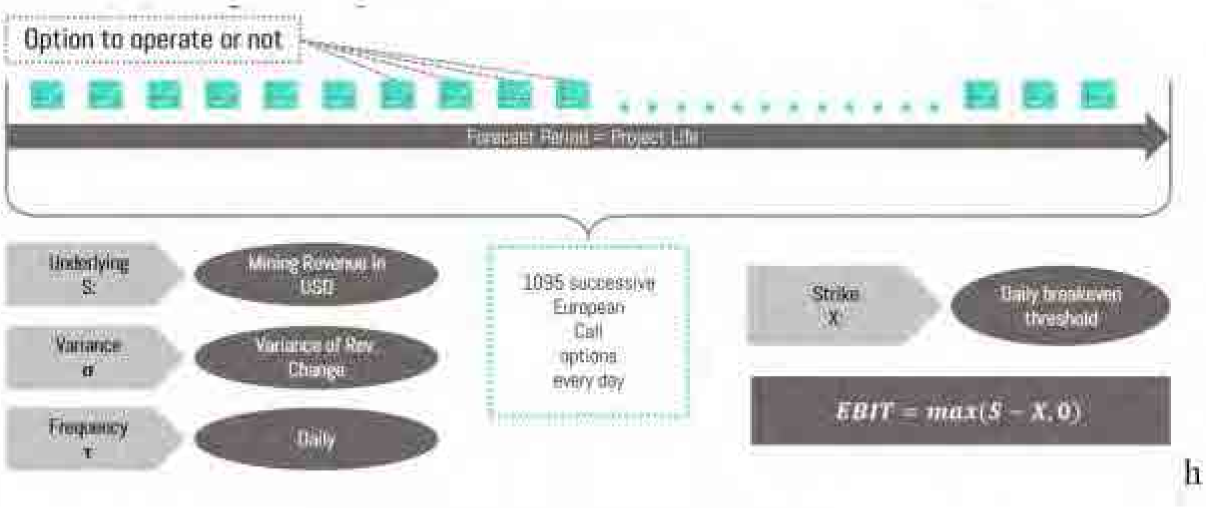



**Fig. 23 Definition of Real Options**

The underlying asset was defined as the revenues of the project is USD. Defined in this way both the effect of BTC price and the Hash rate were captured. Sequential 1095 (one for each day in the life of the project) European call options to earn (capture) the daily revenues if executed. The strike price of the options was defined as the daily costs (mainly) electricity, that had to be expended, if the option was exercised.

A binomial lattice is constructed and the condition for the exercise of any of the options is provided in the following two figures

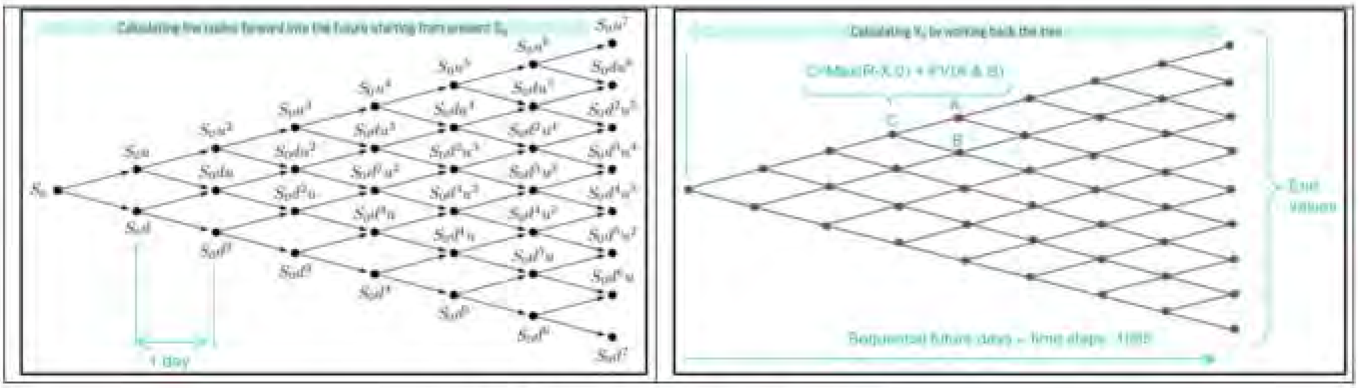
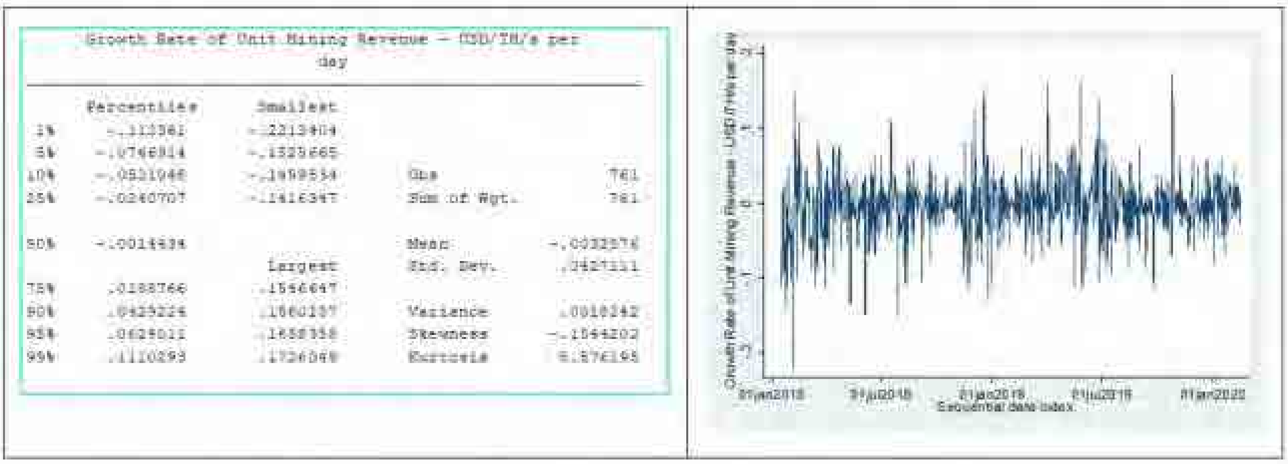


**Fig. 24 Binomial Lattice Approach**

To parametrize the model statistical analysis was performed on Unit BTC mining revenue over the estimation period defined to be two years before the launch of the projects. Results are provided in the following figure.



Growth Rate of Unit Mining Revenue – USD/TH/s per day

| | Percentiles | Smallest | | |
|---|---|---|---|---|
| 1% | -.113361 | -.2213404 | | |
| 5% | -.0746814 | -.1823665 | | |
| 10% | -.0521946 | -.1699534 | Obs | 761 |
| 25% | -.0240707 | -.1416347 | Sum of Wgt. | 761 |
| 50% | -.0014634 | | Mean | -.0032576 |
| | | Largest | Std. Dev. | .0427111 |
| 75% | .0188766 | .1546647 | | |
| 90% | .0425224 | .1660137 | Variance | .0018242 |
| 95% | .0625011 | .1658358 | Skewness | -.1544202 |
| 99% | .1110293 | .1726349 | Kurtosis | 6.376195 |



**Fig. 25 Descriptive statistics of the USD unit mining revenue**

Volatility clustering influenced by BTC/USD volatility pattern as demonstrated by GARCH is evident. Unit mining revenues seem to be hitting a floor which is formed by hashrate coming in and going out as some miners hit marginal costs exceeding marginal revenue. Variance clustering can be modelled in a binomial set up but unlikely to change picture of valuation (As demonstrated by stochastic volatility article) The parameters used for the construction of the tree are presented in Fig.26.

| Input Parameters | | |
|---|---|---|
| Underlying Asset - Rev/THs/day | Vo | 0.166708470 |
| Variance of underlying | σ | 0.04271110 |
| Risk-free rate 2% p.a. | r | 0.00548% |
| | | |
| Discount factor | exp(-r*dt) | 0.99994521 |
| Time (day) | dt | 1 |
| | | |
| Upward move factor | u | 1.0436 |
| Downward move factor | d | 0.9582 |
| Riskneutral Probability Up Move | p | 0.4900 |
| Riskneutral Probability Down Move | 1-p | 0.5100 |

**Fig. 26 Parameters of the binomial lattice**

**4.3 Projected NPV, IRR, and Tobin's Q**

The results of the 2020 valuation were pointing to an approval of the investment. These are presented on Table 6.

| Method | NPV ($ mil.) | Tobin's Q |
|---|---|---|
| **DCF / Single point estimate** | 23.0 | 2.09 |
| **GARCH stochastic simulation** | 17.8 | 1.61 |
| **Real Options Valuation – Binomial Lattice** | 32.4 | 2.94 |

**Table 6: Valuation Results**

All three valuation approaches showed positive NPVs, indicating that the project was financially viable under the modelled assumptions. The estimated Tobin's Q coefficient is greater than unity. This metric is presented here as it is scale neutral. The results were very sensitive to the assumption that were made. Instead of presenting sensitivity analysis which was performed at the time of the valuation a reality check by comparison of forecasts and the actual realisation is a better verdict on the logic, realism and effectiveness of the valuation. Despite the positive NPV estimate, the sponsors of the project decided not to undertake it, the reason being that the value estimates were very sensitive to the evolution of the BTC-Hash rate pair through time.

**5. Forecast versus actual realisation**

To properly assess the adequacy of the 2020 valuation, the forecasts of the main value and uncertainty drivers are compared with their actual realisation during the assumed three-year span of the project. The single-point forecast DCF model is then used to estimate the "would-be" resulting revenues, operating income and free cash-flows had the project been undertaken. The results from this analysis are used for discussion and conclusions.

**5.1 Bitcoin Market Trends (2021-2024): Actual vs. Forecasted**

Bitcoin's prices play a critical role in determining mining profitability. The 2020 valuation model relied on assumptions about BTC price appreciation. We compare the forecasted BTC price path with the actual BTC market movements. Simulated paths versus the real BTC price path are shown on Fig. 27.

The GARCH model was adequate in predicting the BTC price evolution in 2020. However, the 2021 BTC prices outperformed the base-case forecasts significantly, peaking at $64,000 before closing the year at $47,000. 2022 saw a sharp market correction, with BTC falling below $20,000, aligning with Monte Carlo's lower bound scenario. 2023 BTC prices recovered strongly, exceeding most forecasted price paths. 2024 BTC reached all-time highs ($100,000+), far surpassing any forecasted model.

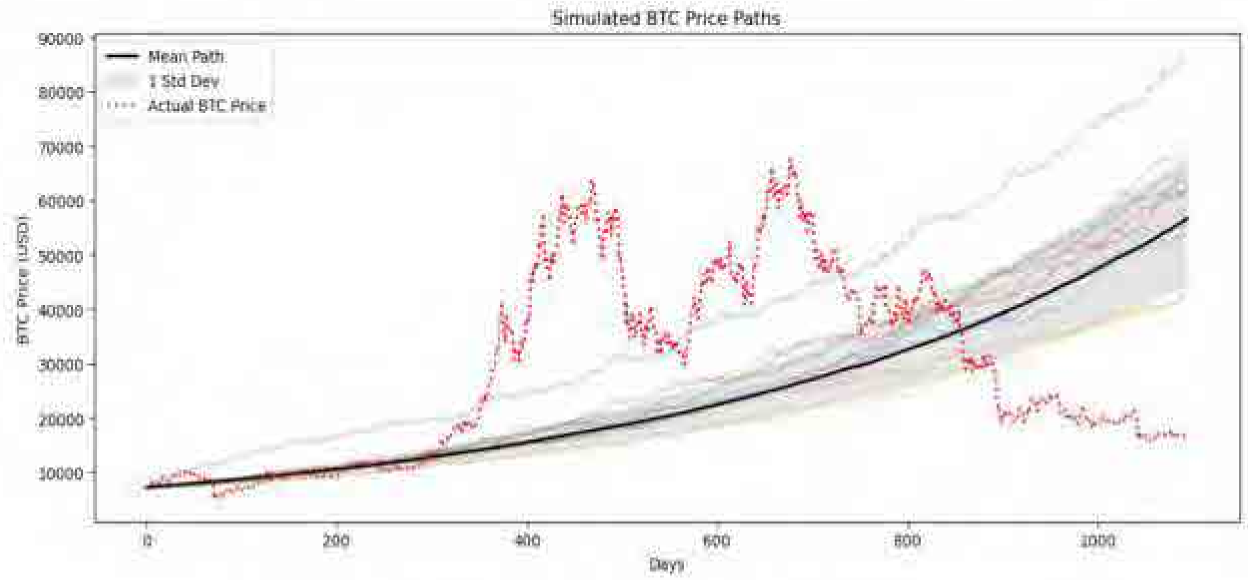



**Fig. 27 Evolution of BTC price – forecast versus actual**

### 5.2 Network Hashrate and Mining Difficulty Growth

Bitcoin mining revenues and resulting profitability depend not only on BTC price but also on network hashrate and difficulty adjustments as seen in their derivation in (1). The more miners compete, the less revenue is allocated to a unit of mining capacity. Hashrate growth in 2021 was lower than expected, meaning Bitcoin Minter would have mined more BTC than anticipated in its first year. This effect is mainly due to the impact of COVID, which shattered the supply chains and ability to install new mining capacity globally. By 2022-2024, hashrate growth far exceeded forecasts, reducing BMF's share of mining rewards more than originally predicted. In effect this reduced the feasibility time span of the project. If BMF had not upgraded its mining equipment, it would have become not competitive at all in later years. Such an upgrade was not envisaged in the original plans.

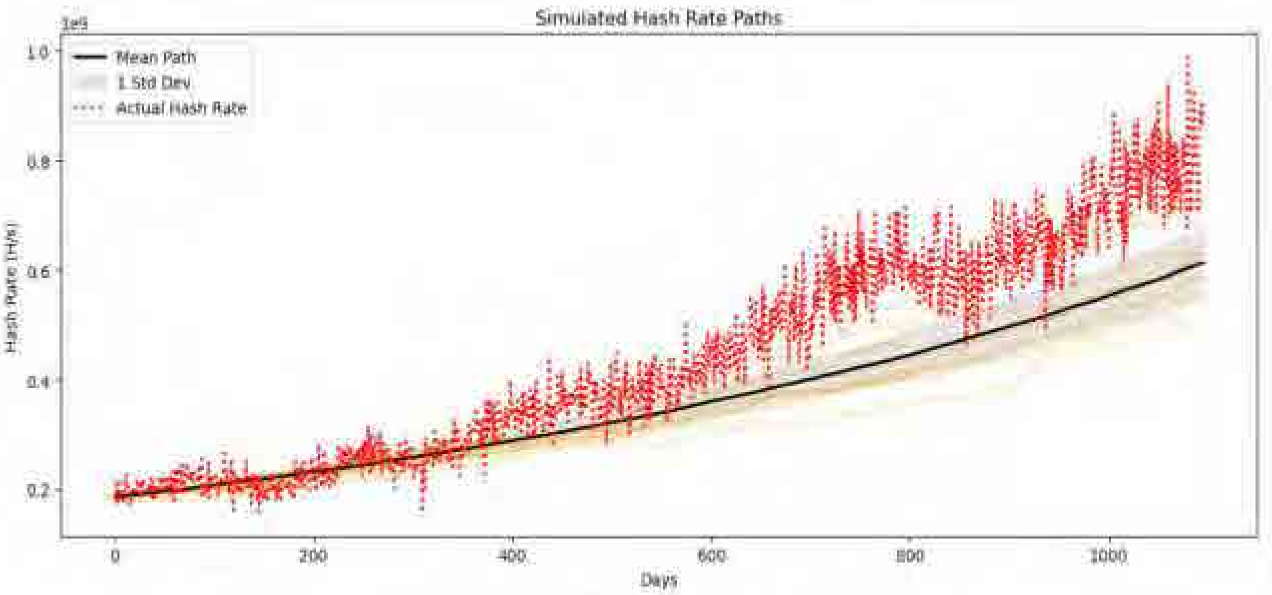



**Fig. 28 Evolution of Hash rate – forecast versus actual**

### 5.4 Would BMF Have Been Profitable? Updated Financial Performance

Using actual Bitcoin price trends, global hashrate growth, and electricity costs from 2021-2024, we now recalculate NPV and Tobin's Q to determine how Bitcoin Minter would have performed if the project had been undertaken. The simulated paths of the revenues, resulting from the joint simulation of BTC and Hash rate are overlaid on the "would" be revenues calculated on joint actual time series for the project's 2020 forecast period.

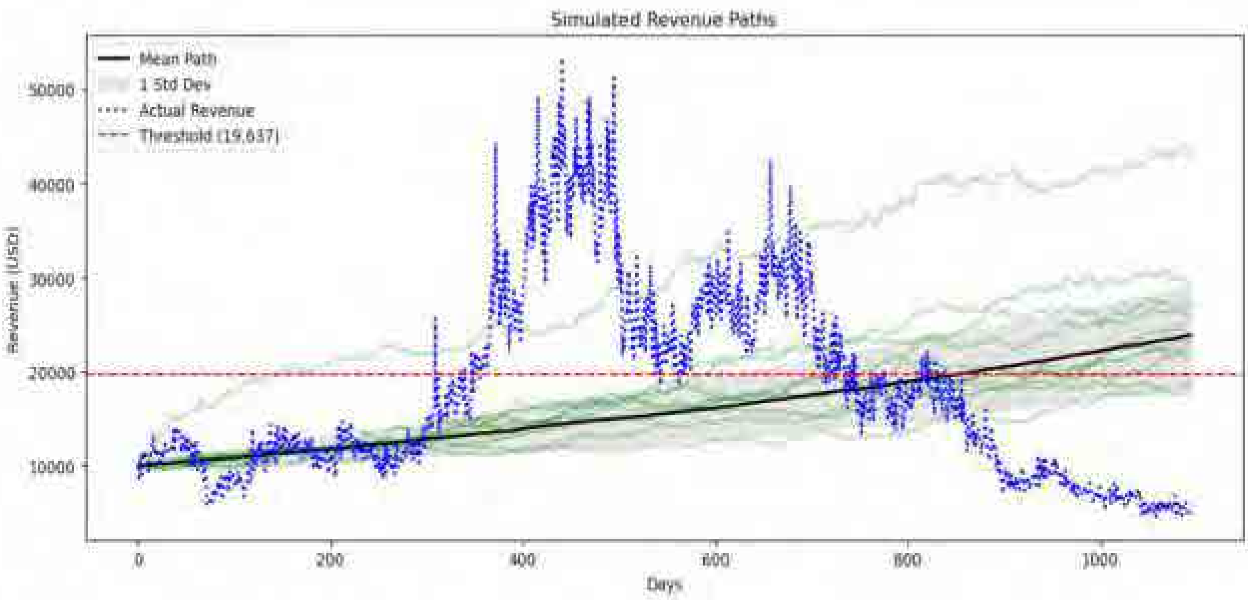



Fig. 29 Evolution of project revenues – forecast versus what would be based on actuals

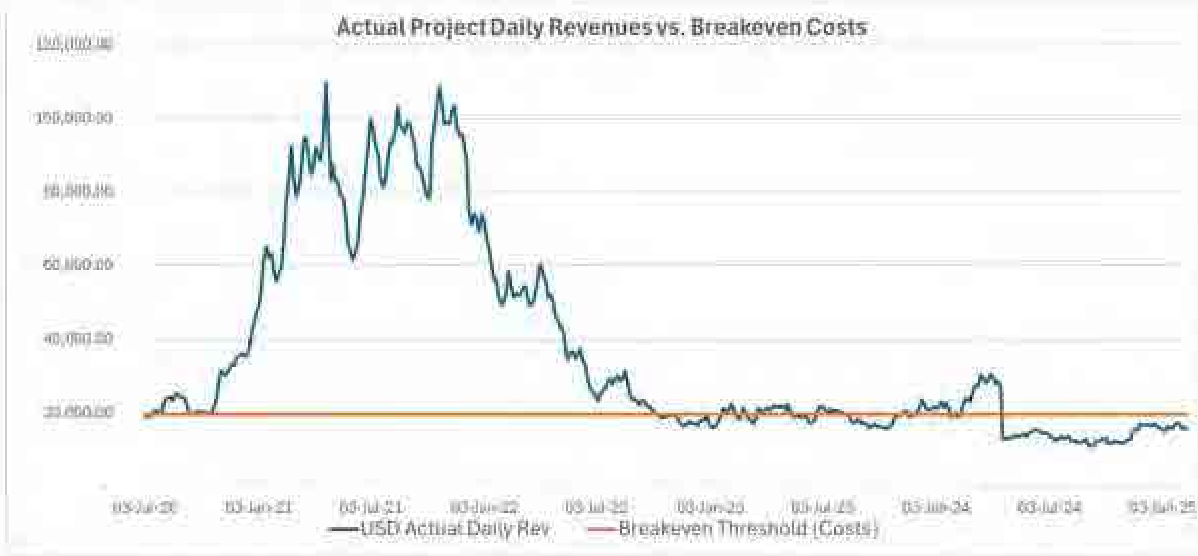



Fig. 30 Evolution of project revenues – forecast versus what would be based on actuals

The project would have performed exceptionally well in 2020-2021 period, but by 2023-2024, mining rewards would have dropped unless additional investments were made in new hardware. The operational flexibility represented by the real Options approach used in the original valuation would have been crucial in deciding whether to operate or not, expand or exit operations. The GARCH simulation used in the 2020 valuation was more proximate to the actual evolution of the Hash rate but altogether underestimated its growth. This estimation error was however compensated by the underestimation of the BTC price evolution as already shown. However, the GARCH simulation altogether failed to predict the substantial upward journey of the BTC price that followed.

| INCOME STATEMENT | Year | 1 | 2 | 3 |
|---|---|---|---|---|
| **Revenues** | | **44,344,192** | **7,610,942** | **7,236,558** |
| **Costs:** | | | | |
| Electriciy costs of BTC mined (COGS) | | -6,571,714 | -6,571,714 | -6,571,714 |
| Monitoring, maintenance and support costs | | -473,473 | -473,473 | -473,473 |
| Staff costs | | -122,400 | -122,400 | -122,400 |
| **Total operating costs** | | **-7,167,587** | **-7,167,587** | **-7,167,587** |
| **EBITDA** | | **37,176,605** | **443,354** | **68,971** |
| Depreciation | | -3,649,691 | -3,649,691 | -3,649,691 |
| **Operating profit** | | **33,526,914** | **-3,206,337** | **-3,580,720** |

**Table 7: "Would be" Income Statement**

The "would be" cash flows of the project against the forecast by the valuation are presented on fig,

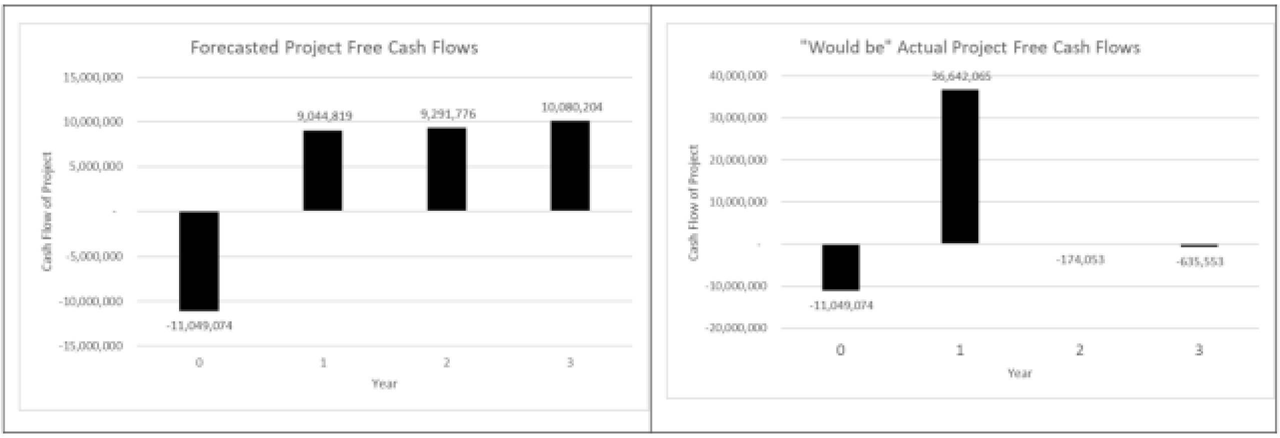



**Fig. 31 Free Cash Flows – Forecasted versus "Would be" based on Actual Realization of BTC and Hash**

On the basis of the recalculated cash-flows using the single-point DCF model but loaded with actual data from BTC and Hash rate, the NPV of the project is $21..64 million with corresponding Tobin's Q of 1.96. This means that the BMF would have been profitable, but not on the back of even closely expected and forecasted scenario. The project would have been paid back during the first year of its operation. This alone raises a lot of questions and issues for discussion.

## 6. Discussion

The 2020 valuation of Bitcoin Minter (BMF) was based on widely accepted financial modelling techniques, yet actual outcomes from 2021 to 2024 significantly outperformed forecasts. This section explores specific areas where the valuation could have been improved, highlighting methodological weaknesses and proposing better approaches for future investment assessments in projects with high uncertainty.

### 6.1 Improved BTC Price Forecasting Accounting for Extreme Scenarios

Based on the sensitivity analysis performed, the Bitcoin and Hashrate projections had the greatest impact on the valuation of the project. Therefore, we have to examine whether the projections could have been made more accurately.

The Monte Carlo simulation with a GARCH model used in the original valuation relied on mean-reverting properties (assuming BTC price fluctuations correct over time) and volatility clustering (large price swings tend to be followed by further volatility). The stochastic process used in forecasting underestimated extreme bull runs. BTC price in 2021 significantly higher than forecasted. The process did not fully capture the speculative nature of BTC. Market cycles in BTC are influenced by hype, institutional adoption, and macroeconomic liquidity.

A better BTC price forecasting model should include regime-switching models (e.g., Markov Chains, recognizing that Bitcoin shifts between low-volatility and high-volatility states. The model should incorporate fat-tailed distributions (e.g., Student's t-distribution), capturing extreme bull and bear cycles better than a normal distribution. The forecast model should also include on-chain and macro factor integration, combining mining difficulty, liquidity cycles, and adoption trends into price forecasting. If the 2020 valuation had applied regime-switching and fat-tailed price distributions, it would have more accurately captured the potential for extreme BTC surges.

**6.2 Better Mining Difficulty & Hashrate Growth Forecasting**

The original valuation assumed a fixed hashrate growth trend (~20-30% per year). It did not factor in market cycle-driven hashrate expansions and impact of COVID which had been a known factor at the time of the valuation. Global hashrate growth after 2022 was much faster than expected, making up for 2021 COVID related supply chain shock, reducing subsequent miners' BTC earnings. Hashrate growth lags behind BTC price movements and this should be taken into account. Miners expand aggressively after bull markets, not before.

A lagged response model for hash rate could have performed better in the forecasting of hash rate evolution. Hashrate should increase in response to past BTC price movements rather than grow linearly. New ASIC chip production (e.g., Bitmain releases) should be included in forecasts. Events like the China mining ban (2021) temporarily reduced global hashrate, boosting rewards for miners who remained operational. This could not have been envisaged. Had the valuation modelled hashrate growth dynamically, it would have better anticipated the increased mining difficulty post-2022.

**6.3 More Sophisticated Risk Management with Real Options**

The Real Options model included in the valuation considered switch-on,/switch-off options but did not actively optimize decision-making under uncertainty. It did integrate adaptive responses to BTC price movements but did not assume reinvestment in new mining hardware. In that respect the model assumed static investment decision-making at the outset, whereas a mining operation should adjust dynamically based on market signals. No structured mechanism for deciding when to scale up vs. reduce operations based on profitability thresholds.

Instead of predefined decision points, the model could have used use adaptive thresholds for expansion, shutdown, switch-on or reinvestment. Machine Learning Profitability Prediction could have been integrated into the option model in order to use historical BTC price, mining difficulty, and transaction fees to predict optimal mining intensity daily. Option to Pre-Sell BTC or Use Hedging Instruments could also have been included. A more adaptive real options strategy could have optimized mining decisions dynamically, further improving profitability.

The Monte Carlo simulation used historical BTC price volatility, assuming future BTC returns would be similar. Consequently, it did not properly capture extreme BTC bull/bear cycles. Extreme price movements were not fully incorporated, leading to flawed NPV estimates. Bayesian Monte Carlo Updating could have been applied to adjust probability distributions as new data becomes available. Machine Learning-Based Parameter Tuning could have optimized Monte Carlo inputs based on macro trends, BTC supply flows, and institutional adoption rates. A more sophisticated Monte Carlo approach could have better captured BTC's extreme volatility, improving price forecasts.

Had these improvements been incorporated into the 2020 valuation, Bitcoin Minter would have had a better uncertainty and risk profile of the investment, even if it was no closer to the “would be” scenario.

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