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A Supply and Demand Framework for Bitcoin Price Forecasting

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Abstract: We develop a flexible supply and demand equilibrium framework that can be used to develop pricing models to forecast Bitcoin's price trajectory based on its fixed, inelastic supply and evolving demand dynamics. This approach integrates Bitcoin's unique monetary attributes with demand drivers such as institutional adoption and long-term holding patterns. Using the April 2024 halving as a baseline, we explore model scenarios with varying assumptions about growth in adoption and supply-side constraints, calibrated to real-world data. Our findings indicate that institutional and sovereign accumulation can significantly influence price trajectories, with increasing demand intensifying the impact of Bitcoin's constrained liquidity. Forecasts suggest that modest withdrawals from liquid supply to strategic reserves could lead to substantial price appreciation over the medium term, while higher withdrawal levels may induce volatility due to supply scarcity. These results highlight Bitcoin's potential as a long-term investment and underline the importance of integrating economic fundamentals into forward-looking portfolio strategies. Our framework provides flexibility for testing different market scenarios, demand curve functional forms, and parameterizations, offering a tool for investors and policymakers considering Bitcoin's role as a strategic asset. By advancing a fundamentals-based approach, this study contributes to the broader understanding of how Bitcoin's supply–demand dynamics influence market behavior.

Keywords: Bitcoin; inelastic supply; economic modeling; inelastic supply; institutional adoption; price forecast; strategic reserve

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1. Introduction

Unlike fiat currencies, which are susceptible to inflationary and debasement pressures, Bitcoin's immutable 21-million-coin supply and independence from central banks position it as a decentralized, independent, enduring, and unique store of value (Ammous, 2018; Antonopoulos, 2015). This may offer investors a tool to mitigate systemic risks arising from inflation, government overspending, and unsound monetary policy, and has important implications for portfolio allocation decisions. While Bitcoin also serves other purposes, acting as a speculative investment and, through Layer-2 innovations such as the Lightning Network (Poon & Dryja, 2016), a medium of exchange, the recent influx of institutional investors and low movement in coins held by long-term investors imply the increasing importance of Bitcoin's role as a global store of value.

Institutional and sovereign investors are particularly important in the Bitcoin ecosystem because even modest allocations by a number of large funds have the potential to drain much of Bitcoin's remaining liquid supply. A supply shock for a store of value with an absolutely inelastic fixed supply is extremely rare. For most commodities, increasing demand causes price to rise, inducing economically marginal producers to enter the market and increase overall commodity supply. With Bitcoin, however, it is not possible to change the supply schedule.

For investors and fund managers considering allocating capital to Bitcoin, there are critical questions to address, particularly regarding what constitutes an optimal allocation to Bitcoin and the risks and benefits of investing in Bitcoin over the long term (e.g., Ang et al., 2022; Baur et al., 2018; Brière et al., 2015; Dyhrberg, 2016; Feng et al., 2018). To make defensible choices, investors need to understand the range of possible future price trajectories for Bitcoin.

Many approaches are available for price modeling, but most rely on statistical analyses that presume that historical pricing provides an adequate basis for future price forecasting. Given Bitcoin's unique situation, characterized by rapidly increasing market demand and an immutable supply schedule, this assumption may not hold. There is, therefore, a pressing need for a Bitcoin pricing model that (1) is based on established supply and demand theory, (2) can be calibrated to observed Bitcoin price performance, and (3) is flexible enough to allow investors to experiment with a range of assumptions regarding price determinants and model parameterization. Bitcoin's future is quite unlikely to resemble its past.

We address these needs by developing a Bitcoin price forecasting framework grounded in the first principles of economic supply and demand theory. The framework provides a large degree of flexibility to adjust model structure, assumptions regarding the functional forms of key relationships, the parameterization of model variables, and the types and levels of uncertainty. The output from our specific model instantiation consists of Bitcoin price forecasts that can then be used as input in forward-looking portfolio allocation models. This is the first attempt we are aware of to apply a fundamental supply and demand-oriented approach to Bitcoin price forecasting. We anticipate that investors will be more confident in their portfolio allocation decisions if price forecasts are based on fundamentals and they can incorporate their own beliefs about market structure and the relative importance of various price determinants.

2. Background

2.1. Bitcoin's Fixed Supply

Bitcoin's unique monetary protocol is governed by a fixed and transparent supply schedule, which ensures that no more than 21 M Bitcoin will ever be issued (Nakamoto, 2008). This feature differentiates Bitcoin from fiat currencies, which are subject to discretionary supply expansions by central banks. Bitcoin's issuance follows a predictable trajectory, with energy-backed block rewards issued to miners (primarily high-performance computing datacenters) halving in size every 210,000 blocks (about four years). Each halving reduces the number of new Bitcoin introduced into circulation by 50%, logarithmically slowing the growth of Bitcoin's new supply issuance over time. The last halving occurred on 20 April 2024, and the next, the fifth, is projected to occur around 19 April 2028.

At the time of the fourth halving, over 93% of the total Bitcoin that will ever exist were already issued, with only ≈1.65 million coins remaining to be mined before reaching the 21 M cap, in about 2140. Despite being early in Bitcoin's overall adoption cycle from a time perspective, the level of current issuance highlights the advanced state of supply saturation and underscores the importance of understanding how constrained supply interacts with evolving demand to shape market prices.

The halving events shape Bitcoin's price trajectory by altering supply and demand dynamics. At the first halving in November 2012, Bitcoin's price was USD 13 per coin. By the time of the fourth halving in April 2024, Bitcoin's price had reached USD 64,858. These dramatic price increases reflect not only the impact of reduced issuance but also the growth in demand driven by broader adoption.

2.2. Bitcoin's Liquid Supply

Not all of Bitcoin's issued supply is accessible to market participants. Bitcoin's 'HODL waves' (e.g., https://www.Bitcoinmagazinepro.com/charts/hodl-waves/, accessed on 28 January 2025), which specify the duration that coins have been dormant, demonstrate the potential impact of long-term holders' behavior on Bitcoin's liquid supply. About 17% of Bitcoin has remained inactive for 10+ years, with an additional 29% held in wallets dormant for 3 to 10 years. Together, holdings dormant for three or more years exceed 45% of the total supply. Some of those have been lost forever due to accidents or deaths. Given anecdotal evidence, it may be reasonable to assume that only about half of Bitcoin's total supply is liquid at this time due to the historical loss and immobility of long-held coins, and the increasing prevalence of reserve-like behavior among newer holders.

Market prices are set at the margin by active traders operating in an environment with a limited pool of Bitcoin available in the short run and an absolutely constrained supply in the long run. A race by institutions and nation-states to create strategic Bitcoin reserves has the potential to rapidly erode the current liquid supply. MicroStrategy's financial engineering strategies—such as issuing low-coupon convertible bonds specifically to fund Bitcoin purchases—demonstrate how credit-driven demand could further accelerate liquid supply depletion (e.g., https://www.youtube.com/watch?v=isZToNExRdY, accessed on 28 January 2025), even in the absence of asset class rotation. Smaller corporations are increasingly allocating Bitcoin to company treasuries, and a large cohort of retail investors continue to accumulate and hold. All signs point to a looming supply shock as Bitcoin's liquid supply is systematically drained from the market.

3. Modeling Options

Projecting Bitcoin's price trajectory requires addressing the interplay between its fixed, perfectly inelastic supply and the evolving dynamics of market demand. As incremental growth in new Bitcoin supply slows, price determination will increasingly depend on factors such as institutional adoption and the withdrawal of HODLed Bitcoin to long-term strategic reserves. These elements introduce complexities that demand a modeling framework capable of linking supply constraints with real-world demand drivers. Several options are available.

3.1. Stock-to-Flow (S2F) Model

The Stock-to-Flow (S2F) model assesses Bitcoin's scarcity by comparing its existing supply (stock) to the rate of new production (flow) (Morillon & Chacon, 2022). Used historically for real estate and precious metal valuation (Shelton, 2024), Bitcoin-oriented S2F models suggest that higher stock-to-flow ratios drive higher prices, with halvings reducing supply growth and increasing scarcity. S2F aligns with Bitcoin's 'digital gold' narrative, offering an intuitive framework for long-term price guidance. While the S2F model intuitively links scarcity to value, out-of-sample performance is weak (Shelton, 2024) and it does not directly account for demand-side determinants like technology adoption trends, macro factors, and new Bitcoin-backed financial engineering.

3.2. Energy-Based Valuation Models

Energy-based models anchor Bitcoin's value to mining costs, suggesting its price reflects the energy expenditure required for production (Hayes, 2019). Rational market pricing thus reflects production costs over time, and the Bitcoin mining costs establish a floor price. By emphasizing production costs, these models offer a tangible, quantifiable basis for price analysis. However, they are not suited to account for Bitcoin's demand-side characteristics, which can decouple market price from production costs.

3.3. Macroeconomic Models

Macroeconomic models analyze Bitcoin's price in the context of global economic indicators, such as inflation, money supply, discount rates, and currency strength (Wang et al., 2023). They hypothesize that Bitcoin behaves as a macro-sensitive asset, similar to gold. However, they overlook internal market dynamics and entirely miss the microeconomic foundations of price determination, limiting the utility of their forecasts unless used as input for two-stage supply and demand equilibrium models.

3.4. Network Models

Network models propose that Bitcoin's value scales according to the size of its user base. These models, drawing on publicly available blockchain transaction data, link adoption growth directly to price, treating Bitcoin as a peer-to-peer economic system where network effects drive value (Chen et al., 2021; Guo et al., 2021; Wheatley et al., 2019). Underlying this approach are a number of key assertions: value grows with network size; adoption data reflect potential value; all users are equally impactful; and there is a direct link from adoption to market price. While network models provide a compelling link between adoption and price, aligning with Bitcoin's growth as a decentralized network, quantifying network models relies heavily on adoption data, which are difficult to define and measure, and may overlook variability in user activity and external economic forces. In Bitcoin's case, there are also challenges arising from the distinct services offered by the base layer (a durable store of value that may not be actively 'used' by investors for years) and Layer 2 solutions that allow for medium-of-exchange services in everyday commerce, as well as a layer of strictly speculative trading that serves to shape short-term market prices at the margin.

3.5. Power Law Models

Power law models (Newman, 2005) suggest Bitcoin's price follows growth patterns driven by network scaling effects (Wheatley et al., 2019). In the power law modeling approach, price follows non-linear (log–log) scaling. In the Bitcoin space, power law modelers suggest that Bitcoin price will stabilize over time and see diminishing returns as Bitcoin is integrated into the existing financial system. While useful for highlighting historical patterns, explaining the factors that drive power laws is debated (Newman, 2005; Gabaix, 2009). Power law models that statistically describe Bitcoin's historical price growth are unable to anticipate the timing or implications of the pattern breaking down: they are descriptive, not predictive, in that they provide no insights regarding the direct impact of particular determinants on market price.

3.6. Quantitative and Statistical Models

Quantitative models apply time series econometric techniques to historical Bitcoin data to identify trends and make probabilistic forecasts (Ciaian et al., 2016). Statistical time series models (Hendry, 1986) focus on patterns in past price movements to infer future trends, and they can be extremely good at forecasting price movements and estimating elasticities in the short term. However, their focus on lagged and short-term dependencies may fail to capture Bitcoin's long-term growth trends and prioritize uncontextualized statistical variances over grounded supply and demand dynamics.

3.7. Supply and Demand Equilibrium Models

The supply and demand equilibrium modeling approach, long a mainstay approach in production economics (Beattie et al., 2009), treats Bitcoin as a commodity with fixed supply and growing demand, whatever its source, and calculates market-clearing equilibrium price paths. In advanced models, it is possible, for example, to handle exogenous factors such as policy shifts and unexpected shocks (e.g., Askari & Krichene, 2010).

4. Methodology

We develop a discrete supply and demand equilibrium framework that can be used to evaluate Bitcoin's long-term price potential, anchoring price path forecasts in its inelastic supply and growing demand. A scarcity-driven dynamic distinguishes Bitcoin from traditional assets, making supply constraints central to understanding its value, particularly as institutional and sovereign adoption expands. Different kinds of models can be implemented within the framework; in this paper, we use a discrete daily model to develop vectors of forecast Bitcoin prices under different parameterization assumptions.

4.1. Modeling Framework and Context

We set 20 April 2024, the date of the fourth halving, as the framework's starting point. Our current effort is based on the conjecture that a perfectly inelastic (vertical) supply curve and a constant elasticity of substitution (CES) demand curve can be used to forecast equilibrium market price trajectories. In our framework, a model's parameterization is highly flexible, easily allowing for exploration of a range of options for all key assumptions (as well as modifications to functional form and time horizon).

As of 20 April 2024, we know the total historic issuance (q_0 = 19,687,500 Bitcoin) and market price (p_0 = USD 64,858). We also know the average daily issuance levels beyond the start date (450 Bitcoin/day for the halving 04 epoch, 225 for epoch 05, and 112.5 for epoch 06). Bitcoin equilibrium prices are forecast by calculating the intersection of the CES demand curve and inelastic supply curve, each of which are updated based on the daily issuance schedule for newly minted Bitcoin, varying levels of Bitcoin withdrawals to long-term storage, and growing market demand.

4.2. Bitcoin Supply Curve

The distinguishing characteristic of the Bitcoin supply curve is that it is vertical and perfectly inelastic (Figure 1). In any given time period, the quantity of Bitcoin available for issuance (mining rewards) cannot be increased: the supply curve is fixed vertically at the level of available liquid supply. Bitcoin miners' only possible response to higher market prices arising from growing market demand is to intensify their mining effort to capture a larger portion of the pie. The size of the pie—total Bitcoin mining rewards—is, however, immutable due to Nakamoto's (2008) design.

The curvature in the demand function implies larger increases in Bitcoin price when liquid supply falls relative to smaller decreases in price when supply increases by an equal amount; this asymmetry is particularly pronounced as liquid supply approaches zero (where the demand curve also asymptotically approaches zero).

We do not, however, know the number of lost or permanently HODLed Bitcoin, so we must estimate those. For example, Satoshi's 'lost' stash is generally estimated to be in the 1.1 M Bitcoin range, and other lost coins may account for up to as much as another 4 M Bitcoin. Of the remaining circulating Bitcoin, perhaps another 3 to 4 M are in the hands of investors with no explicit intention to sell.

For the 20 April 2024 start date, we assume that Bitcoin's liquid supply equals total issuance less the sum of Bitcoin: (1) held in Satoshi wallets (1,000,000 Bitcoin); (2) lost (4,000,000 Bitcoin); and permanently HODLed (3,500,000 Bitcoin). Unfortunately, there are no precise numbers for lost coins available, but our numbers are consistent with current speculation (e.g., https://store.bitbo.io/blogs/wallets/lost, accessed on 28 January 2025) and easily modifiable using the framework. Given these assumptions, liquid supply in the baseline model is set at q_0 = 11,187,500 Bitcoin.

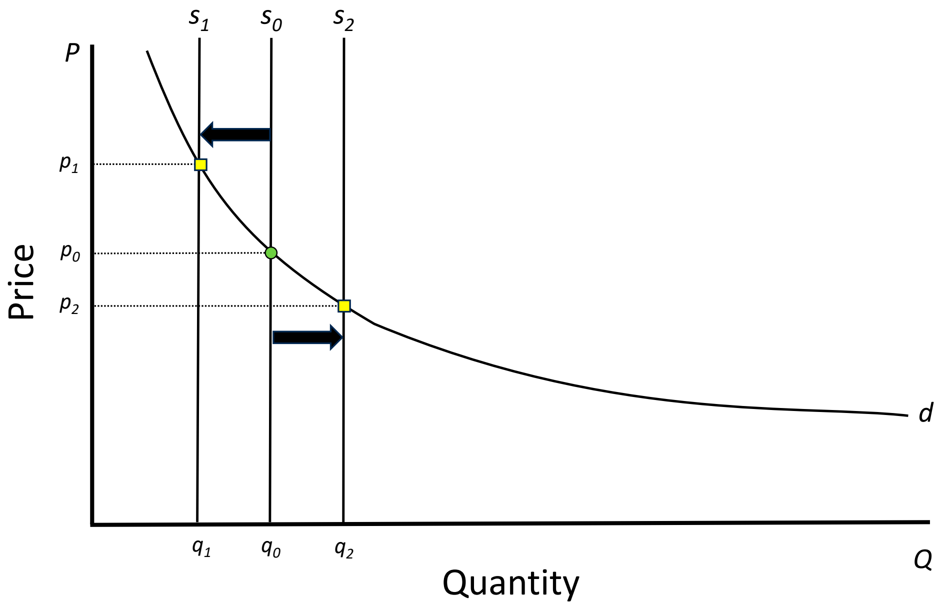

Figure 1. Changes in equilibrium quantity traded and market price as supply changes and the demand curve, *d*, is fixed. A decrease in supply (e.g., purchase for a long-term Bitcoin strategic reserve) leads to a reduced quantity (left arrow) and higher price (q_1, p_1) in the face of a fixed demand, *d*; an increase in supply (e.g., mining rewards being issued; HODLed coins coming back into the market) leads to an increased quantity (right arrow) and a lower price (q_2, p_2).

Going forward, and adding a term to account for Bitcoin withdrawn from liquid supply to permanent reserve funds, liquid supply, q_l, on any particular date is calculated as

$$q_{l(t)} = q_0 + \sum_{t=1}^{T} q_{emissions(t)} - q_{satoshi} - q_{lost} - q_{hodl} - \sum_{t=1}^{T} q_{reserve(t)} \quad (1)$$

where q_l = liquid Bitcoin supply; q_0 = Bitcoin issued as of April 20, 2024; $q_{satoshi}$ = total Bitcoin in Satoshi wallets; q_{lost} = lost Bitcoin supply; q_{hodl} = existing permanently HODLed coins at the fourth halving; $q_{reserve(t)}$ = the cumulative number of Bitcoin withdrawn permanently from circulation; and $q_{emissions(t)}$ = the cumulative issuance from 21 April 2024 up to, and including, the current time period.

For any given level of liquid supply, there are families of unobservable demand functions passing through an observed price point (Figure 2). In a young, rapidly evolving Bitcoin market, there is no good option to statistically test and identify a preferred functional form and empirically estimate model parameters. However, we can 'reverse engineer' a demand curve, picking a functional form that is theory-based and economically reasonable. Once chosen, it is then further possible to identify model parameterization combinations that result in the observed market price and presumed level of liquid supply.

The reason we need a valid demand function, such as the CES (even if we are unable to assess the 'best' demand function), is because we know that it will reflect reasonable trade-offs between quantity and price as the liquid supply of Bitcoin is depleted.

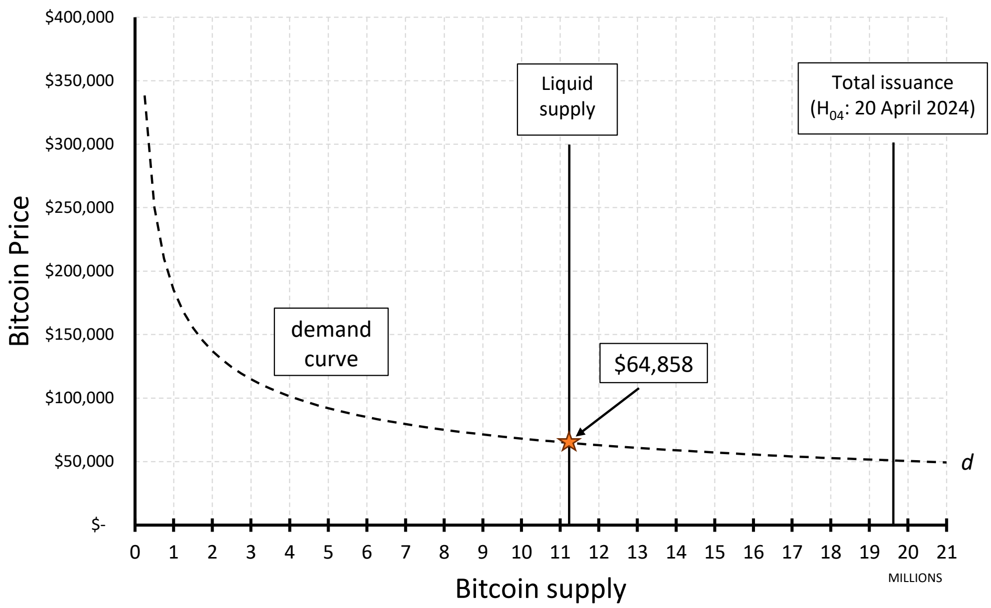

Figure 2. Demand curve definition: given an assumed liquid supply of 11,187,500 Bitcoin and the observed market price on 20 April 2024 (fourth halving), it is possible to back-calculate possible combinations of parameters that define theoretically valid demand curves.

4.3. Bitcoin Demand Curve

Using a theoretically valid demand function is important in Bitcoin models for several reasons. First, various demand functions (Barten, 1977) are based on fundamental axioms of choice, so they are based firmly in utility theory and reflect human behavior. Second, several popular demand functions are easy to work with mathematically and, when adequate market data are available, statistical tests can assess how well a demand curve fits observed data. Third, demand functions can take account of factors other than the price and quantity of a single good, so the scope for understanding complex price determinants may, in the future, be accounted for. For example, demand functions can account for multiple complementary or competitive goods (e.g., Bitcoin and gold) and nested levels of demand (e.g., for stores of value, first, and Bitcoin's share of the total, second).

4.3.1. Constant Elasticity of Demand

We chose to use a CES demand function for a single commodity:

$$P_b = A{Q_b}^{1/\varepsilon} \tag{2}$$

where P_b denotes Bitcoin price and Q_b denotes liquid supply. There are two parameters in the function: A is a demand shifter, where increasing A pushes the demand curve outwards, giving a higher equilibrium price for any given Bitcoin supply, $q_{l(t)}$, at time t, and ε is an elasticity scaling parameter that controls the steepness of the CES demand function.

4.3.2. Elasticity

Recall from Figure 2 that we have an observed price point from 20 April 2024, the date of the fourth halving. If we assume that the liquid Bitcoin supply on that date is q_0 = 11,187,500, it is possible to set one parameter and solve for the other (Figure 3), giving combinations of A and ε that result in p_0 = USD 64,858 for that level of liquid supply. For any A, ε can be calculated as

$$\varepsilon = {}^{ln(q_0)}\!\big/_{ln(p_0/A)} \tag{3}$$

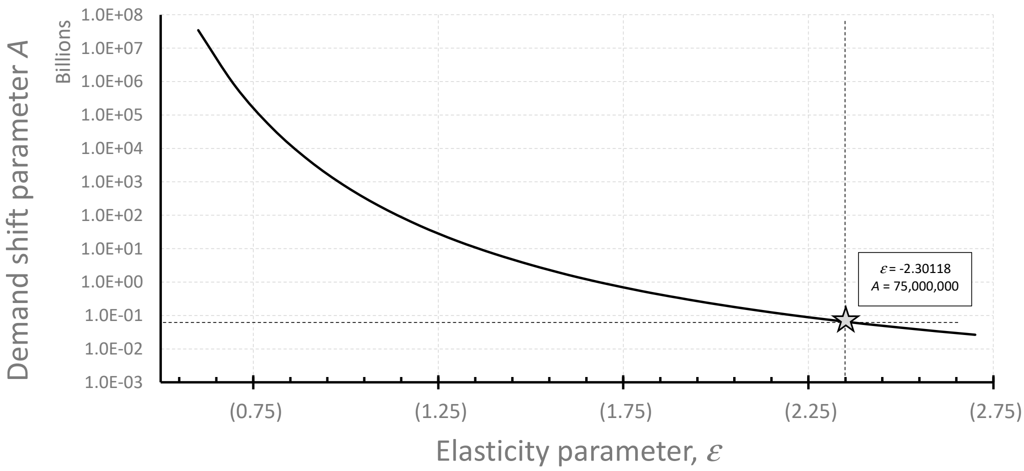

Figure 3. Combinations of ε and A that give a Bitcoin price p_0 = USD 64,858 in the CES demand function. For our baseline model, we set A = 75 M and $\varepsilon = -2.301$.

The choice of the final combination of parameters for our baseline model is arbitrary but can be informed by choosing a Bitcoin elasticity value that is in a 'reasonable' range. Bitcoin is a young asset and still widely viewed as a risk-on, speculative investment. It seems sensible that it would exhibit relatively high demand elasticity now but that it could become much more inelastic, behaving with less price sensitivity, over time, more like traditional stores of value.

For our baseline model, we chose to fix A = 75,000,000, thus implying elasticity, $\varepsilon = -2.301$. For context, gold demand in India is highly inelastic, with short-run elasticity estimated at $\varepsilon = -0.588$ (Immanuvel & Lazar, 2021). All combinations calibrate to p_0 = USD 64,858 as of the framework's 21 April 2024 start point.

4.3.3. Demand Shift

Assumptions about the demand shift parameter, A, also impact Bitcoin price. With a CES demand function, there is a linear relationship between A and equilibrium market price. If one is choosing A based on a target elasticity range, it is important to be aware that less elastic demand implies higher levels of A and, thus, higher market prices for Bitcoin if all other parameters remain fixed.

4.4. Model Development

We used Lumina System's Analytica platform (https://analytica.com/ accessed on 28 January 2025), which can account for uncertain parameters (Morgan & Henrion, 1990) influencing Bitcoin's price determination, to implement this model. Analytica has recently been used widely for other Bitcoin-oriented research that features high levels of uncertainty (Rudd et al., 2024).

For our baseline model (Figure 4), we assume a 12-year time horizon starting with the fourth halving on 20 April 2024 and ending at the seventh halving on about 16 April 2036; a supply curve initially positioned at q_0 = 11,187,500 Bitcoin on 20 April 2024; a market price of USD 64,858 on 20 April 2024; and a CES demand function with parameters A = 75,000,000 and $\varepsilon = -2.30118$.

The orange trapezoids (start date; end date; supply issued at t = 0; and observed market price at t = 0) are fixed in this model (but can be customized when developing new models). The BTC daily issuance variable uses projected daily Bitcoin mining rewards and anticipated halving dates to tally the subsequent new Bitcoin issued daily after the fourth halving. The Total to reserve variable keeps a running daily tabulation on total withdrawals, and Liquid supply sums total Bitcoin issuance to date less coins removed from circulation. Variables in the demand-side module calculate CES demand function parameters. The magenta hexagonal shapes are output metrics, including the daily Bitcoin forecast price (2024 US dollars); total asset value ([market price] × [total issuance]); and compound annual growth rate (CAGR).

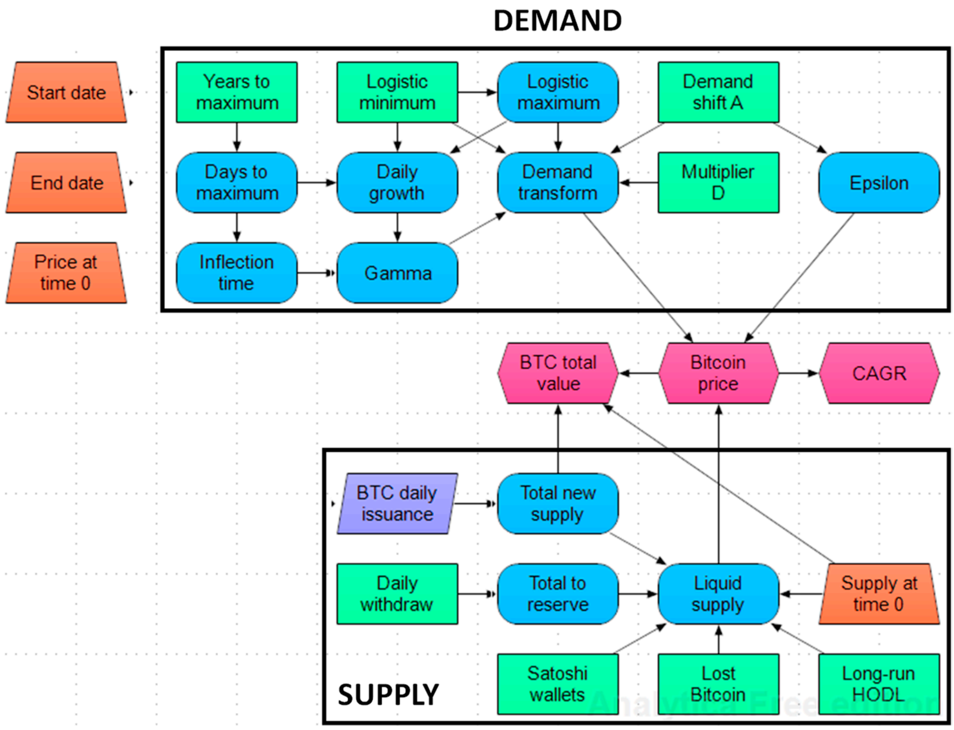

Figure 4. Overview of model structure, including calculation of demand and supply, and derivation of forecast Bitcoin price, total asset value, and CAGR performance metrics. The model was implemented using Lumina System's Analytica platform (https://analytica.com/ accessed on 28 January 2025).

The green rectangles are choice variables, which allow for a variety of assumptions regarding supply and demand to be compared; they were defined as discrete levels in this model but also could easily be defined as statistical distributions. The options, with the default baseline model parameters in bold, are as follows:

1. Logistic function time horizon (years to 'saturation' in a logistic function), T^* = [4, 6, 8, **10**, 12, 14 years];
2. Logistic function minimum (influencing the stage where one is in the adoption cycle), L_Min = [0.01, 0.02, 0.03, **0.04**, 0.05, 0.06, 0.07, 0.08, 0.09, 0.10];
3. Demand shift parameter (chosen to align with beliefs regarding CES elasticity—recall Figure 3), A = [50 M, **75 M**, 100 M, 150 M, 250 M, 500 M, 1 B, 10 B, 100 B, 1 T, 10 T, 100 T, 1 Q, 10 Q, 100 Q];
4. CES demand multiplier (growth in demand), D = [**1**, 10, 20, 30, 40];
5. Bitcoin withdrawn daily to reserve after April 20, 2024, $q_{reserve}$ = [**0**, 1000, 2000, 2000; 3000; 4000];
6. Bitcoin held in Satoshi wallets as of April 20, 2024, $q_{satoshi}$ = [750 K, **1.00 M**, 1.25 M];
7. Lost Bitcoin as of April 20, 2024, q_{lost} = [2.0 M, 3.0 M, **4.0 M**, 5.0 M];
8. Permanently HODLed Bitcoin as of April 20, 2024, q_{hodl} = [1.5 M, 2.5 M, **3.5 M**, 4.5 M].

The compound annual growth rate (CAGR) was calculated as

$$CAGR = \left(\left({}^{p_T}\!/_{p_0} \right)^{\frac{1}{T/365}} \right) - 1 \quad (4)$$

where p_T is the forecast price at the end of the model's 12-year time horizon.

To accommodate growth in demand over the duration of the model's time horizon, our modified demand shift parameter, A', increases in magnitude smoothly over time. We use a logistic curve, often used to model growth or adoption curves (Rogers, 1962), to transform the constant demand shift parameter A into A':

$$A' = {}^{\gamma_t A}\Big/\left(1 + e^{-r(t-t^i)}\right) \tag{5}$$

where A' = transformed (growing) logistic CES demand parameter, A = original (constant) demand shift parameter, r = daily growth rate, t = time (days) since t_0 (20 April 2024, fourth halving), t^i = inflection time, and gamma (γ_t) = logistic transformation parameter that increases over time.

Several extra steps were needed in order to calculate γ. First, we defined baseline parameters for the logistic cumulative density function (cdf), working with a baseline of a 10-year time horizon, T^* (not to be confused with the model's overall 12-year time horizon). The logistic cdf is symmetric, so the midpoint, t^i, defines the date the inflection point is reached, at which time the growth rate starts to decelerate.

In the baseline model, we assumed that the default value for the transformation was *L_Min* = 0.04 at t_0; the saturation parameter, *L_Max*, an upper saturation target, is then 0.96 (*L_Max* = 1 − *L_Min*). Both *L_Min* and T^* can easily be adjusted in the framework to customize Bitcoin adoption trajectories. Choosing *L_Min* = 0.10 would give almost straight-line growth from t_0 to T^*, while *L_Min* = 0.01 would give a very sharp S-curve close to the inflection point, T^i. A low value of *L_Min* implies being early in the technological adoption curve.

Next, we calculated the daily growth rate (needed later for the A' calculation):

$$r_{daily} = \left[ln\left({}^{1}\big/_{L\_max}\right) - 1\right] - \left[ln\left({}^{1}\big/_{(1 - L\_max)}\right) - 1\right] \Big/_{(365 * T^*)} \tag{6}$$

where r_{daily} = daily growth rate, *L_max* = (1 − *L_min*), and T^* = 10 years.

The logistic transformation function, γ, was calculated using the upper saturation target and daily growth rate:

$$\gamma = {}^{L\_max}\Big/\left(1 + e^{-r_{daily}*(10*365/2)}\right) \tag{7}$$

Finally, the minimum value at the start of this curve, *L_min*, needed calibration to 1.0 for integration into the CES demand function:

$$A' = 1 + \left({}^{(D-1)}\Big/_{(L\_max - (1 - L\_max\ ))}\right) * (\gamma - (1 - L\_max)) \tag{8}$$

When the demand multiplier $D > 1$, A' will exhibit accelerated Bitcoin price appreciation over time, with options of up to 40X growth in the demand shift multiplier. Figure 5 shows trajectories for the various multipliers applied to the transformed demand shift parameter, A'.

Daily reserve withdrawal options from Bitcoin's liquid supply are $q_{reserve}$ = [0, 1000, 2000, 3000, 4000], corresponding to total withdrawals over the model's time horizon of 0, 4.38 M, 8.76 M, 13.13 M, and 17.51 M, respectively. We recognize that the daily removal of 3000 or more Bitcoin would drain the entire liquid supply and cause a pricing singularity—we retain the levels for current modeling but refrain from inferring any price forecasts for scenarios that approach a hyperbolic price increase, and we address some options for tempering this in the future (see Section 6.4.1). Figure 6 shows the erosion in liquid Bitcoin supply under differing assumptions.

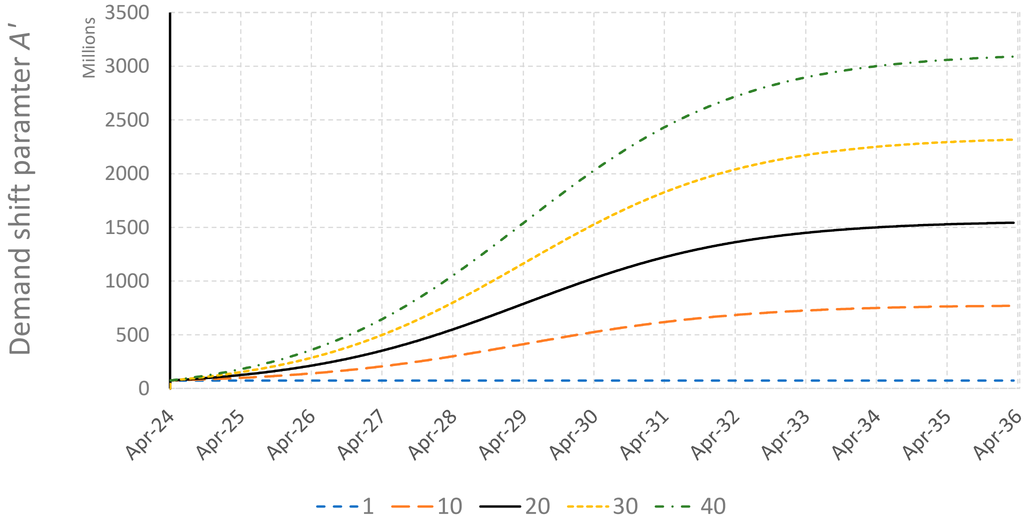

Figure 5. Transformed logistic demand shift parameter, A', with smooth growth from parameter default value (A = 75 M) to 10X, 20X, 30X, and 40X the baseline value.

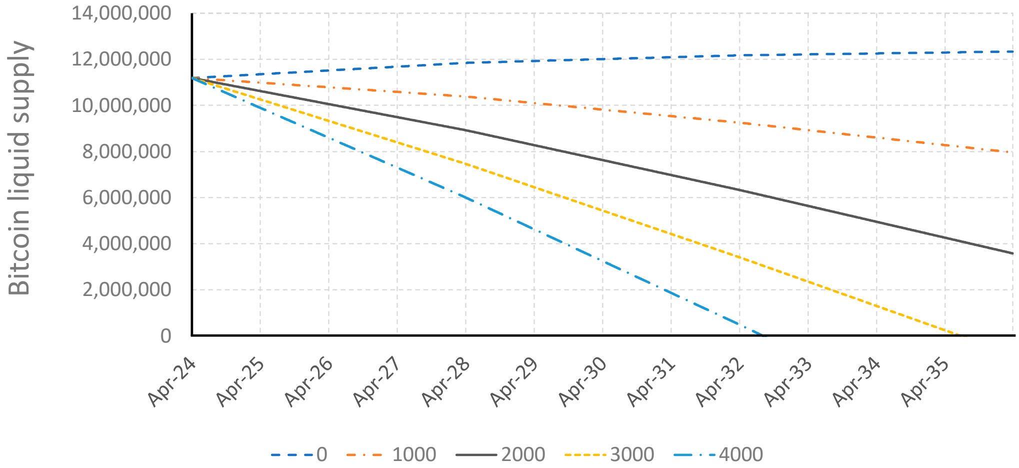

Figure 6. Bitcoin liquid supply with different daily withdrawal rates. Note that with zero withdrawals to reserve, the liquid supply increases slightly due to newly minted Bitcoin being awarded to miners over the coming years.

5. Results

5.1. Changes in Forecast Price with Changes in Single Parameter Values

5.1.1. Changes in Demand Shift Parameter

We allow for different demand multiplier parameterization value levels of up to D = 40. The Bitcoin market price is forecast to be USD 62,160, USD 638,890, USD 1,279,701, USD 1,920,511, and USD 2,561,322 for demand multipliers of D = [1, 10, 20, 30, 40], respectively, while withdrawals are held steady at zero. The D = 1 parameterization projected Bitcoin price will fall slightly by the end of the time horizon because there is a small but steady stream of newly issued Bitcoin adding to the liquid supply over the years. While the upper end of the range may seem extreme, it is clear that even in the absence of liquidity constraints, rapidly expanding market demand for Bitcoin alone has significant potential for price appreciation.

The total market value of Bitcoin at the baseline parameterization is USD 1.3 T. Thus, a 40X multiplier would increase Bitcoin's total asset value to USD 53.4 T. For context, gold's total asset value was around USD 16 T in November 2024 (see https://youtu.be/4LqpGrWGNqE, accessed on 28 January 2025). A USD 16 T total asset value for Bitcoin, matching gold, would require A to be 940,000 (12.53X from baseline), implying an equilibrium Bitcoin price of about USD 813,000 in the absence of supply-side impacts due to dwindling supply.

5.1.2. Increased Withdrawal to Permanent Storage

Figure 7 shows the impact of different withdrawal levels from the liquid supply, which accounts for Bitcoin coming off the market and being put into permanent strategic reserves or long-term storage, while all other parameters are held at their baseline levels.

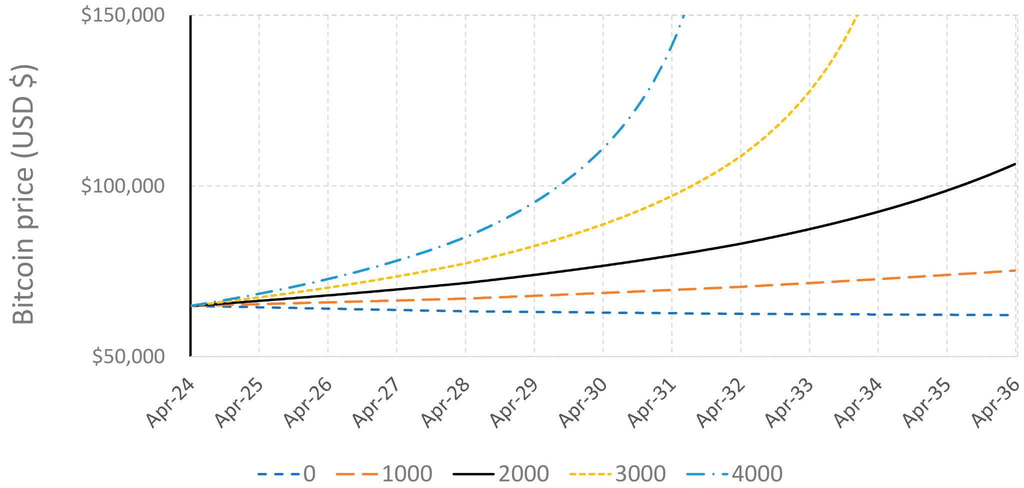

Figure 7. Projected price with varying levels of withdrawal from Bitcoin's liquid supply while assuming all other parameters in the model are held steady at baseline values.

If the baseline level of liquid supply (11,187,500 Bitcoin) falls by 2000 Bitcoin per day, the price impact of increasing scarcity is clearly visible (solid, middle line). With all other baseline model assumptions held steady, the forecast Bitcoin price is USD 106,401, a 1.64X multiple from the observed price on 20 April 2024. For the upper levels of withdrawal, price increases hyperbolically as the supply is exhausted, so it is not useful to consider their ultimate prices as realistic targets (see Discussion). For context, Senator Cynthia Lummis has proposed a bill which would have the US government create a strategic reserve of 1 M Bitcoin, purchasing 200,000 Bitcoin annually, equivalent by itself to almost 550 Bitcoin per day over 5 years.

The range of price impacts depends heavily on the liquid supply of Bitcoin, particularly as withdrawals increase to more than 2000 per day and total liquid supply falls below about 2 M Bitcoin. Our current assumptions regarding lost and HODLed coins and levels of withdrawal to reserves suggest a supply shock is more likely in the medium rather than the near term, if demand were to stay similar to that of the April 2024 baseline.

5.2. Changes in Bitcoin Price with Simultaneous Changes in Parameters

Figure 8 shows forecasts for Bitcoin prices when the demand multiplier and reduction in liquid supply are both allowed to vary simultaneously. For all charts in this section, withdrawal levels of 3000 and 4000 Bitcoin per day are not included because they exhaust liquid supply and cause hyperbolic price increases prior to the end of the 12-year time horizon. The striking result is the impact of the combination of large drawdowns in liquid supply and high demand multipliers on equilibrium market price, even when daily withdrawal rates are not high enough to exhaust liquid supplies.

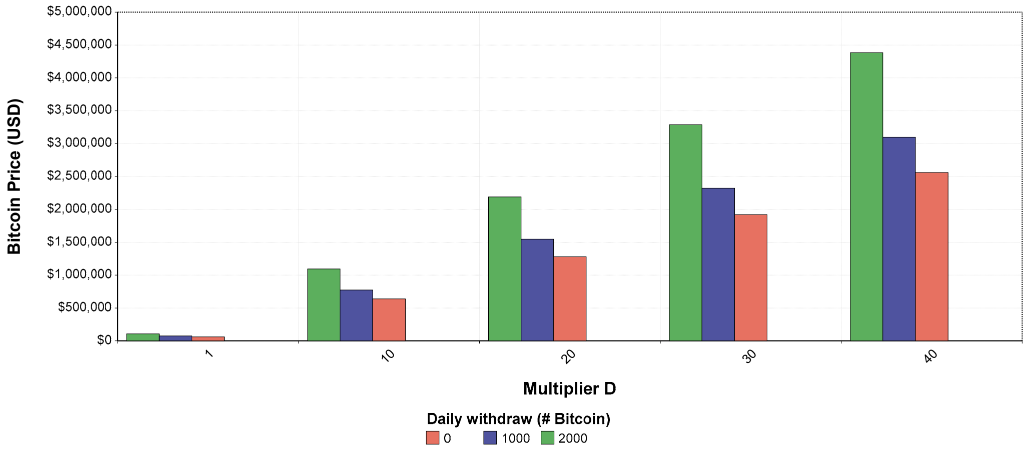

Figure 8. Forecast prices for 16 April 2036 (seventh halving) with variable demand shift multipliers (D = [1, 10, 20, 30, 40]) in combination with varying levels of daily Bitcoin withdrawals from liquid supply (qreserve = [0, 1000, 2000]).

Table 1 shows the predicted prices for each combination shown in Figure 8. For additional context, US ETFs alone have been buying a net long-term average of about 285 Bitcoin per day as of mid-December 2024 (https://treasuries.bitbo.io/etf-flows/, accessed on 28 January 2025); many of those Bitcoin will likely be permanently lost to liquid supply.

Table 1. Forecast Bitcoin prices for April 2036 under varying combinations of demand shift multiplier (D) and assumptions regarding total removals from liquid supply. Withdrawal levels of 3000 and 4000 Bitcoin per day are not applicable because liquid supply was exhausted, causing hyperbolic price increases, prior to April 2036.

Demand Multiplier	Daily Withdrawal (# Bitcoin) from Liquid Supply				
	0	1000	2000	3000	4000
1X	USD 62,160	USD 75,203	USD 106,410	n/a	n/a
10X	USD 638,890	USD 772,947	USD 1,093,690	n/a	n/a
20X	USD 1,279,701	USD 1,548,217	USD 2,190,667	n/a	n/a
30X	USD 1,920,511	USD 2,323,488	USD 3,287,645	n/a	n/a
40X	USD 2,561,322	USD 3,098,758	USD 4,384,623	n/a	n/a

Figure 9 shows Bitcoin's total asset value for the same combinations used for the price forecast calculation.

Bitcoin's overall asset value could reach as high as USD 91.4 trillion (almost 6X gold's current USD 16 trillion value) with a demand shift multiplier of D = 40 and liquid supply reduction of 2000 Bitcoin per day (Table 2). That level of daily removal would still leave liquid supply at 3.58 M Bitcoin by April 2036, but increasing to 3000 per day would exhaust Bitcoin liquid supply prior to the seventh halving. Reaching the current USD 16 trillion total asset value of gold would take only a 10X demand shift multiplier combined with about 1000 Bitcoin of daily withdrawal from liquid supply.

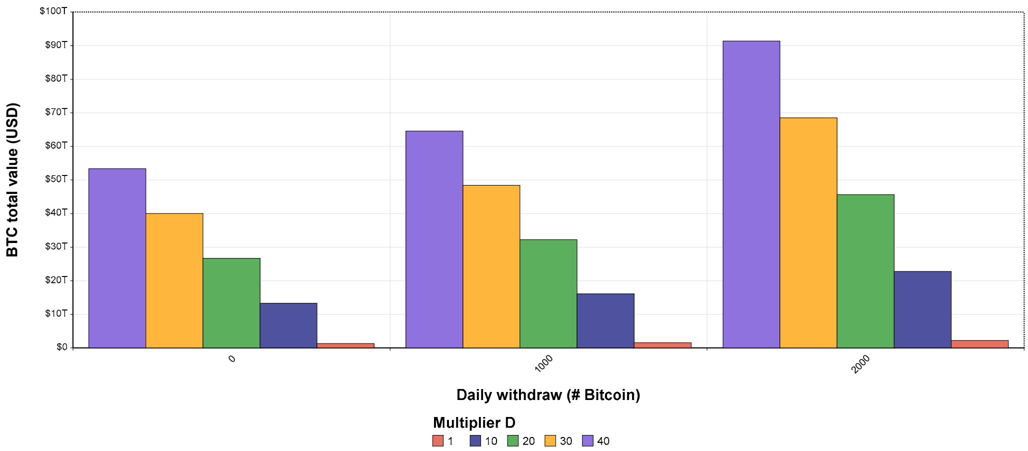

Figure 9. Total asset value for Bitcoin under varying combinations of demand shift multiplier and daily withdrawals from liquid supply.

Table 2. Predicted Bitcoin total asset value (trillion USD) for 16 April 2036 under varying combinations of demand shift multiplier (*D*) and assumptions about total removals from liquid supply. Withdrawal levels of 3000 and 4000 Bitcoin per day are not applicable because liquid supply was exhausted, causing hyperbolic price increases, prior to April 2036.

Demand Multiplier	Daily Withdrawal (# Bitcoin) from Liquid Supply				
	0	1000	2000	3000	4000
1X	USD 1.3 T	USD 1.6 T	USD 2.2 T	n/a	n/a
10X	USD 13.3 T	USD 16.1 T	USD 22.8 T	n/a	n/a
20X	USD 26.7 T	USD 32.3 T	USD 45.6 T	n/a	n/a
30X	USD 40.0 T	USD 48.4 T	USD 68.5 T	n/a	n/a
40X	USD 53.4 T	USD 64.6 T	USD 91.4 T	n/a	n/a

5.3. Bitcoin Price Trajectory

Switching to Bitcoin's evolving price trajectory, the primary output needed for forward-looking portfolio analyses, the choices regarding model parameters' 'reasonable' ranges will depend on the beliefs of a modeler. Given the ease with which this framework facilitates adjustments, one option is to periodically (i.e., monthly, quarterly) recalibrate, assessing which combination of parameter values would result in recent observed market prices.

Scenario 1: *conservative assumptions based on December 2024 performance.*

As we write this (mid-December 2024), the Bitcoin market price is USD 102,000. From a market perspective, there has been strong ETF demand in the USA throughout 2024, suggesting that the demand shift parameter, *D*, could already be substantially larger than it was in April 2024, and/or the logistic curve time horizon parameter, T^*, may have decreased, bringing demand-based growth forward in time. Additionally, it seems reasonable to assume that there will be an evolution towards a less elastic Bitcoin demand curve over time.

We first set A = 150 M, thus fixing elasticity at $\varepsilon = -2.0953$, in a revised, slightly less elastic demand function. Following a similar procedure to that used for the baseline model, we explored parameter combinations that gave prices in the USD 100,000 range for 15 December 2024. We found one 'reasonable' combination with $\varepsilon = -2.0953$, $L\_Min = 0.04$, $T^* = 8$ yrs, and $D = 20$. With this combination, our conservative scenario, Bitcoin prices under varying levels of withdrawals from liquid supply are forecast at USD

98,577 (0 withdrawals) to USD 102,808 (4000 per day) as of 15 December 2024. Maintaining these parameter values going forward for the balance of the 12-year time horizon gives us a conservative scenario for forecasting prices (Figure 10).

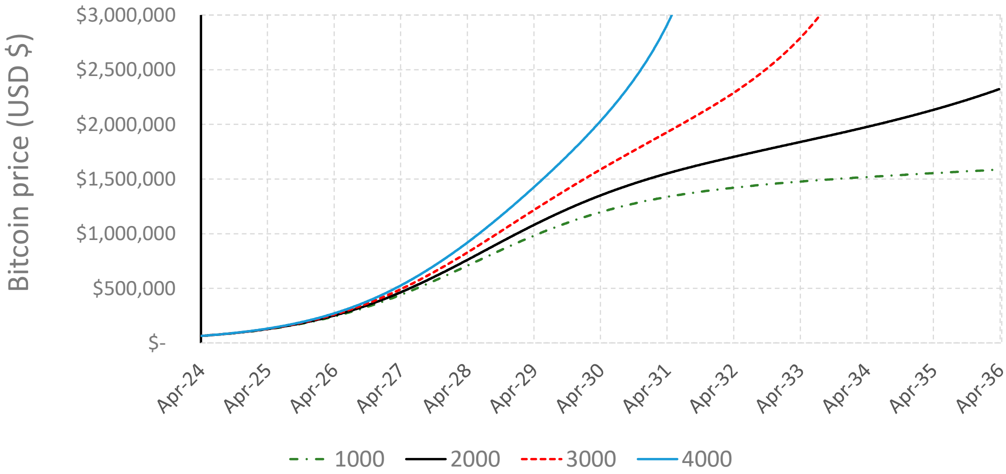

Figure 10. Forecast price trajectory for our conservative scenario, which uses parameter values consistent with an updated USD 102,000 Bitcoin market price observed in mid-December 2024.

This scenario implies that the Bitcoin price could reach the USD 1 M level by about June 2028, providing that there are continual strong flows of 4000 Bitcoin being removed from liquid supply daily. For an intermediate level of withdrawal—2000 Bitcoin daily—the USD 1 M mark is forecast to be breached by early Autumn 2028. Supply shock is noticeable by the 2029–2030 range for the highest level of withdrawals, signaling accelerating price appreciation (again with the caveat that we recognize this rate of withdrawal may not continue as Bitcoin price increases at an increasing pace). We hypothesize that this is where an upside break of the power law would most likely appear in the conservative scenario.

Scenario 2: *Bull scenario based on rapidly growing institutional adoption.*

Current (December 2024) market conditions further suggest that a wave of institutional adoption is building for 2025 and beyond. This implies our Scenario 1 assumptions, based on mid-December 2024 conditions, are likely quite conservative. Very recent market developments that illustrate incoming institutional demand include the following:

- NASDAQ recently (13 December 2024) announced MicroStrategy's inclusion in the Nasdaq 100 (QQQ) index listing, which will trigger some USD 3.1 B of new capital flows into MicroStrategy stock (opening up possibilities for the company to aggressively purchase more Bitcoin);
- FASB accounting standard changes come into effect on 15 December 2024;
- Numerous US states are drafting bills, being tabled in early 2025, to establish strategic Bitcoin reserves (https://www.satoshiaction.io/sbr, accessed on 28 January 2025);
- The incoming Trump administration has signaled support for a US federal government strategic reserve;
- There has been rapidly growing international interest in strategic reserve funds.

All of the following factors suggest a more aggressive bull market model parameterization was in order:

- L_Min = 0.02 (suggesting we are still early in the adoption curve);
- A = 500 M (thus fixing $\varepsilon = -1.8134$ and reducing demand elasticity as price-insensitive institutional and sovereign investors become more prevalent);

- T^* = 6 yrs (reflecting strong incoming demand and competition among institutional investors);
- D = 30 (equivalent to one more step change of the same magnitude as the difference between the April and December 2024 demand expansion).

Figure 11 shows forecast prices when the demand multiplier is held constant (D = 30) and daily withdrawal rates from liquid supply vary. At the highest level of withdrawal, there is a clear trend from the logistic-style, adoption-driven curve to one that starts to increase on a hyperbolic trajectory (see Section 6.4.1). This parameterization suggests that Bitcoin will reach USD 1 M prices by early 2027 for all levels of withdrawal >1000 Bitcoin per day, and then diverge in 2028 as supply constraints come into play. With the higher levels of withdrawal, the price could reach USD 2 M by late 2027 and USD 5 M by early 2031.

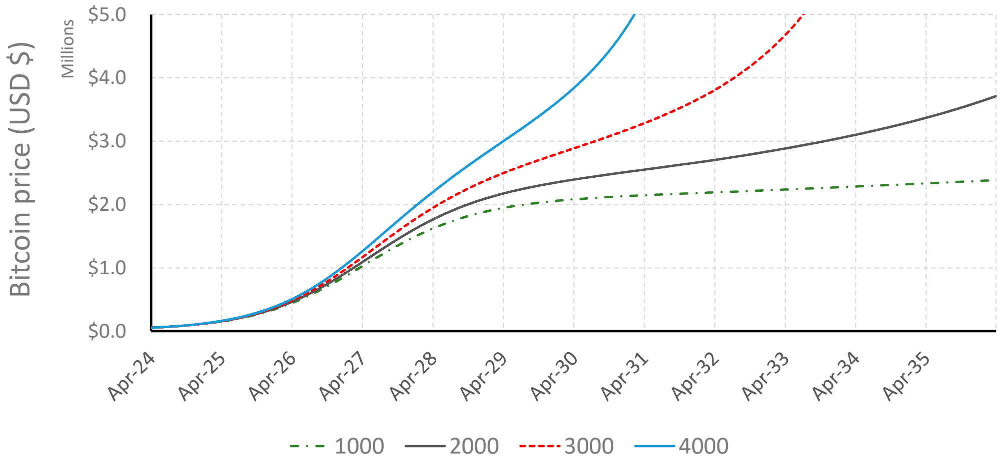

Figure 11. Forecast Bitcoin price over time with varying levels of total removals from liquid supply when demand shift D = 20, e = −1.8134, and T* = 6 yrs.

The CAGRs for these scenarios reach as high as 40.2% when 2000 Bitcoin are withdrawn daily from liquid supply in combination with an increase of 30X in the demand shift parameter (Figure 12). For perspective, Bitcoin's historical CAGR over the last 13 years was 99.5% (see https://curvo.eu/backtest/en/market-index/bitcoin?currency=usd, accessed on 28 January 2025).

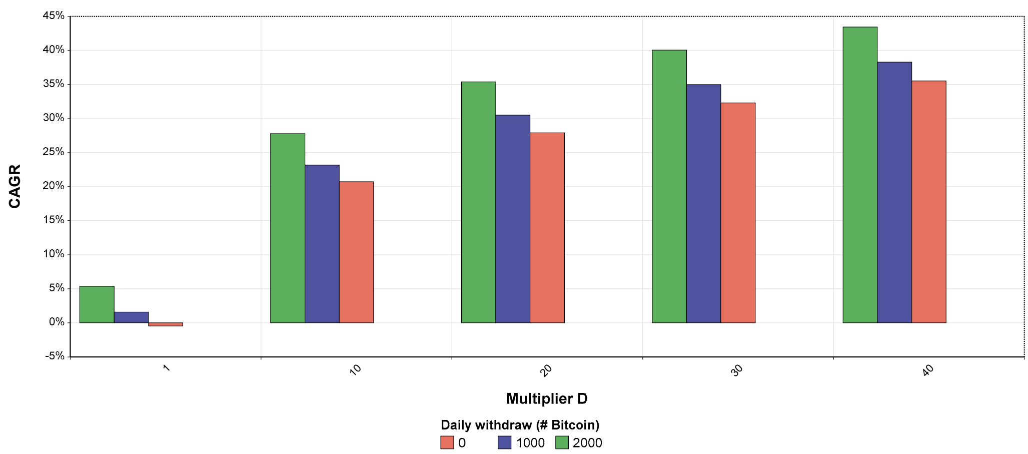

Figure 12. CAGR under various combinations of parameterization for A and liquid supply withdrawal (e = −1.8134 for all scenarios; CAGR was not calculated for higher withdrawal levels, which exhausted liquid supply prior to April 2036).

6. Discussion

We developed a Bitcoin price forecasting framework based on fundamental supply and demand principles. A vector of credible forecast prices would be invaluable for fund managers considering portfolio allocations to strategic Bitcoin reserves. Starting from economic first principles, our supply and demand framework integrates Bitcoin's fixed, inelastic supply with a CES demand function. Specific models can, in the future, be constructed using customized parameterization, alternative CES elasticities, and new insights regarding liquid supply. The framework can also be adjusted to use alternative, more sophisticated demand functions and different time horizons.

After calibrating a specific baseline model using April 2024 data, we explored how shifts in market demand and Bitcoin liquid supply might impact future price dynamics. In our conservative scenario, we further adjusted the parameterization based on a December 2024 recalibration; we also created an additional bull scenario in which more aggressive parameterization values were explored.

Our results show that Bitcoin's price is highly sensitive to withdrawals from liquid supply and shifts in the market demand parameter. Even modest changes in institutional adoption could generate significant price appreciation in the short to medium term. Bitcoin's perfectly inelastic supply curve also implies that the pace of withdrawals from liquid supply to long-term reserve funds will have a strong influence on Bitcoin price appreciation and volatility over the medium to long term. While preliminary, our model provides price forecasts (https://doi.org/10.6084/m9.figshare.27997877.v2, accessed on 28 January 2025) that could help investors develop forward-oriented portfolio allocation models, illuminating Bitcoin's potential role in long-run strategies for institutional and government investors.

6.1. Growth in Demand

Bitcoin's growing adoption by institutional investors and sovereign wealth funds signals a transformative shift in its demand landscape. As institutions allocate Bitcoin within their portfolios, they amplify demand in ways that fundamentally alter market dynamics. The demand shift parameter, A', in the CES demand curve can help capture the impact over time of increasing demand-side adoption on Bitcoin's price. While our emphasis in this paper is on institutional adoption, it is important to recognize that shifting market demand, whatever its source (for value transfer, speculation, etc.), has the potential to affect Bitcoin's demand curve expansions and contractions, thus having important marginal price impacts. Relatively small shifts in investors' beliefs and behavior may become particular important once supply becomes highly constrained, when price volatility may increase.

With a 10X increase in the demand shift parameter over the model's time horizon, our model forecasts Bitcoin's price could surpass USD 600,000, even in the absence of withdrawal from Bitcoin's liquid supply, demonstrating the baseline effects of increased adoption. Further periodic calibration or empirical estimation of A' is possible, increasing confidence in adjusted price forecasts in the future. In the short run, increasing demand appears to exert substantially more influence on Bitcoin prices relative to reductions in liquid supply.

Emerging financial mechanisms driven by credit creation could increase Bitcoin demand. Through corporate debt issuance, structured financial products, and collateral-backed borrowing, institutions might fund Bitcoin acquisitions using newly created credit rather than reallocating capital from other assets. This dynamic structurally shifts how demand for Bitcoin expands, potentially making the demand shift parameter A' larger than we initially anticipated. Even without precise quantification, recognizing this mechanism reframes Bitcoin's growth not as a zero-sum competition with traditional assets but as part of a broader expansion of the financial system's liquidity.

While we simply adjusted the demand shift parameter, D, in an ad hoc way in this model, to illustrate the range of plausible price impacts from shifting supply and demand, it will be possible in the future to use statistical analyses (e.g., macroeconomic or time series analyses) to model D in terms of real-world drivers of Bitcoin demand.

6.2. Liquid Supply

As large investors accumulate Bitcoin for permanent strategic reserves, they will likely withdraw substantial quantities of Bitcoin from the market. In our baseline model, the price impact of falling liquid Bitcoin supply was more relevant for intermediate- to long-term horizons. However, a near-term race by nation-states and institutional investors to accumulate Bitcoin before it becomes truly scarce may change this, bringing a supply shock forward in time.

Our findings emphasize that institutional adoption dynamics are not merely additive but catalytic, with the combination of rising institutional demand and falling supply having the potential to drive dramatic price increases. This appears especially true as liquid supply falls below 2 M Bitcoin. In a full-blown supply shock, the key interactions between supply and demand occur where the perfectly inelastic supply curve intersects the increasingly inelastic region of the demand curve, implying high levels of price volatility for small changes in liquid supply or minor shifts in overall market demand.

Even if we are mistaken about our initial choice of parameters A and ε, or our estimate that 40–50% of the total supply has already been removed from the liquid supply, our results suggest (barring unforeseen Black Swan events—always a possibility) that steep price appreciation is coming but that the timing is uncertain. Lost coins, including early wallets with inaccessible keys and Satoshi's holdings, represent permanent reductions in supply. Long-term HODLing further intensifies scarcity as Bitcoin increasingly becomes a reserve asset rather than a transactional or speculative investment. As Bitcoin becomes more integrated with traditional finance, selling pressure may also decrease as it becomes useful as collateral for Bitcoin-backed loans. New derivative trading opportunities for Bitcoin and Bitcoin ETFs may also influence liquid supply by enabling long-term HODLers to retain their Bitcoin rather than selling into market strength during bull market peaks.

These factors raise the question of what happens to the Bitcoin price as it becomes absolutely scarce. As Figure 11 showed, Bitcoin price forecast trajectories go hyperbolic as the levels of relatively modest daily Bitcoin removal from liquid supply accelerate. Of course, not all institutional purchases will be permanently removed from circulation, but Figure 11 illustrated that perfectly feasible daily Bitcoin withdrawals could exhaust supply within our model's 12-year time horizon.

Our analysis reflects the relative value of Bitcoin versus the US dollar, so a hyperbolic price increase implies that the dollar experiences a collapse in purchasing power relative to Bitcoin. Some factors may, however, dampen the effects. As prices rise, it is likely unreasonable to assume that a steady flow of thousands of coins will continue to be removed each day from the liquid supply. With Bitcoin at much higher prices, the number of coins removed could fall drastically, even while investment levels grow in USD-denominated terms.

Additionally, Bitcoin's elasticity parameter will likely change over time as it evolves from a speculative asset to a long-term store of value. Even when the elasticity parameter is set to the most inelastic option in our framework, $\varepsilon = -0.86086$, there is more advance warning of hyperbolic price appreciation, but inelastic demand alone does not eliminate the possibility of runaway price appreciation within a similar time frame. Instead of curtailed volatility and decreasing returns over time, as the power law implies, our results suggest that extreme volatility should be expected and that the power law relationship will break down as liquid supply falls under about 1 to 2 M Bitcoin.

6.3. Modeling Results in Context

Validating our supply and demand framework against alternative approaches could enhance its credibility. Triangulating results from different kinds of price forecasting models can help identify areas of convergence, bolster confidence in predictions, and highlight gaps for refinement.

MicroStrategy's approach demonstrates how institutional Bitcoin accumulation can be driven by credit expansion rather than being based solely on asset reallocation: they are actively issuing billions of dollars of corporate bonds and engaging in equity offerings specifically to acquire Bitcoin. Their macro-oriented 'Bitcoin24' model (available at https://github.com/microstrategy, accessed on 28 January 2025), which is based on assumptions regarding Bitcoin's evolving asset class value relative to established asset classes, has a baseline price forecast of a USD 13 M Bitcoin price by 2045, with an intermediate 2036 price target and overall asset total value of USD 2.4 M and USD 55 trillion, respectively. That is close to our model when parameterized with a 20X demand multiplier and daily withdrawals of about 2250 Bitcoin, and only slightly more aggressive than our conservative scenario. Our forecast Bitcoin price at a USD 55 trillion total market value is about USD 2.7 M, slightly higher than MicroStrategy's price target at the same total market value.

MicroStrategy's bull forecast has an intermediate 2036 price forecast of USD 6.6 M and a total asset value of USD 140 trillion. This is substantially above the parameterization combinations in our bull scenario (e.g., Figure 11 assumptions of D = 30 and daily withdrawals of 2000 Bitcoin, which led to USD 68.5 T in total asset value). Their model supports the idea that a combination of demonetizing other assets and credit expansion can lead to very high Bitcoin market prices over time. Bitcoin's CAGR in MicroStrategy's full model, out to 2045, is 29.2% and 37.5% for their baseline and bull models, respectively. By comparison, our 2036 CAGR estimate for 2000 Bitcoin per day withdrawal levels and D = 40 was 43.6% over the bull scenario's shorter time frame.

One current estimate of the power law model (see https://charts.bitbo.io/long-term-power-law/, accessed on 28 January 2025) forecasts a 2036 Bitcoin price of about USD 2.1 M (based on late November 2024 data) should historic scaling remain constant. That corresponds to our model's price forecast when D = 20 and withdrawals are marginally under 2000 Bitcoin per day.

These three models come at Bitcoin price prediction from entirely different perspectives but are surprisingly close in their 2036 price forecasts, signaling that our current supply and demand-oriented approach is both representative of historical price trends and in line with forward-looking projections from the corporation most deeply engaged in Bitcoin accumulation and financial engineering.

We also note that ARK Invest's price forecast is USD 3.8 M per Bitcoin by 2030 (https://www.investors.com/news/why-cathie-wood-sees-bitcoin-price-soaring-to-3-8-million/, accessed on 28 January 2025). While we do not have access to their pricing model, Cathie Wood's statements imply that the USD 3.8 M figure is based on institutional investors allocating 5% of their portfolio holdings to Bitcoin. Without specific details about the ARK Invest model, it is not possible to assess which parameterization would be needed in our model to arrive at a similar price, but it does appear that our demand shift multiplier would need to be substantially larger and/or liquid supply would have to soon be constrained to less than 1 M Bitcoin.

6.4. Limitations and Future Research

6.4.1. Modeling Issues

Several model limitations suggest areas for further research. First, the assumption of fixed elasticity of substitution may oversimplify the interplay between market conditions and price sensitivity. With the single-commodity CES functional form and our choice to calibrate to specific values of ε and A', our price forecasts provide only a narrow slice from the very large space of possible demand curves and parameterizations. Future research could explore alternative demand functional forms, including those that capture substitution effects using either CES or other valid functional forms.

Quantifying the demand curve from empirical data is likely to remain difficult in the near to medium term. However, it may be possible to construct demand functions using a stated preference approach. This would involve survey research, presenting decision-makers with structured scenarios that vary in their risks and rewards. These choice experiment surveys allow for the construction of theoretically valid demand functions based on random utility models (Brownstone & Train, 1998). Additional calibration points—quarterly or semi-annually—might be added to the model over time to further narrow the combinations of parameters that align with the prior price trajectory.

Second, our model relies on uncertain estimates of lost coins. Improved methodologies for identifying inactive wallets or applying probabilistic approaches to refine lost coin estimates would enhance the model's precision. We must also recognize that some 'lost' coins may come back to market if Bitcoin prices rise so much that long-inactive HODLers are enticed to sell. There are also challenges in capturing long-term HODLer intent regarding their holdings. Current data provide snapshots of HODLing trends but lack detail on the motivations and strategic considerations of long-term holders. For example, coins held in cold storage might be used as collateral for loans, making them appear dormant while remaining part of the financial system's credit base.

Third, the framework does not account for structural changes in Bitcoin's network dynamics. Layer 2 solutions, like the Lightning Network (Martinazzi & Flori, 2020; Poon & Dryja, 2016), could alter Bitcoin's utility and valuation should it become a global medium of exchange. This poses a modeling challenge as there need not be any set scaling relationship between Lightning and Bitcoin transaction volumes. It remains unclear the extent to which Layer 2 applications might impact supply and demand dynamics on Bitcoin's base layer, and how that might be modeled.

Fourth, credit-driven institutional 'demand shocks' could cause sudden increases in our CES demand shift parameter, reflecting the creation of entirely new liquidity pools through debt issuance. Recognizing this type of new demand highlights the need for refined models that reflect the possibilities for upward demand-side liquidity shocks.

Fifth, the possibility of hyperbolic growth in Bitcoin's price needs close attention. This may be an artefact of our first-generation model, one that will be alleviated with further refinements to functional form and parametrization. If, however, the forecast prices continue to exhibit hyperbolic tendencies in future iterations of this model, that would suggest Bitcoin's price appreciation has the potential to cause market volatility and seriously disrupt financial systems, perhaps leading to damaging levels of competition (i.e., a Bitcoin 'arms race') and adverse social and geopolitical outcomes. There are existing tools (e.g., derivatives) that can help constrain volatility in mature markets, as well as the potential for innovative new tools (e.g., international Bitcoin reserves that release Bitcoin during extreme market conditions) or even government regulatory actions. These are all complex and could be the focus of future research.

Sixth, the model's use of highly uncertain parameters highlights the need for further calibration and testing as we develop more understanding about the distributions of important variables. Certainly, monthly or quarterly recalibrations that capture supply and demand trends are possible, but it would also be possible to incorporate stochasticity into the model using Monte Carlo simulations or by developing ensemble-oriented Decision-Making under Deep Uncertainty (DMDU) models (Groves & Lempert, 2007; Marchau et al., 2019). Those could provide more refined representations of potential price trajectories and the relative importance of particular price determinants in the face of high levels of uncertainty. Scenario modeling (e.g., Groves & Lempert, 2007; Hulme & Dessai, 2008) may also be useful to help identify key risks and outcomes and develop narratives that could help illustrate potential societal outcomes when important factors vary along key axes.

6.4.2. Forward-Looking Portfolio Allocation Modeling

With a foundational modeling framework established, integrating Bitcoin price predictions into forward-looking portfolio allocation simulations should follow. Different kinds of institutional investors and policymakers may hold very different assumptions about market conditions and adoption trajectories, as well as having different investment mandates. The framework's customization options help to ensure that bespoke models can provide salient information for diverse stakeholders.

6.4.3. Expansion of Analyses for Other Cryptocurrencies

The framework that we developed focused specifically on Bitcoin because of (1) its market dominance; (2) the high levels of institutional interest in Bitcoin over 2024; and (3) the unique characteristics of its fixed supply schedule. While supply and demand-oriented frameworks could be developed for various other digital assets, their supply and demand framework would need to be different from Bitcoin's because they have varying levels of ongoing inflationary token emissions. Presumably, our framework could serve as inspiration for others researching various other cryptocurrencies, but they cannot be modeled in the same way as Bitcoin within this framework.

7. Conclusions

In this paper, we address the critical need for Bitcoin price forecasting that is based on fundamental economic principles. It is not yet possible to econometrically test the performance of various demand curve functional forms to identify the best fit; however, adopting a CES functional form, which is commonly used in applied economics, provides a theory-based option that, at minimum, specifies valid relationships between supply and demand and their price trajectory implications. For investors and governments considering funding strategic Bitcoin treasuries and reserves, this approach may be more credible than those based primarily on historical pricing trends or more ad hoc statistical analyses.

A key result from our initial model—that, with sufficient withdrawals of liquid supply to strategic reserves, hyperbolic Bitcoin price increases may be a possibility—underscores the urgent need for individuals, firms, and governments to consider Bitcoin investments and portfolio allocations, as well as the exploration of financial risk management tools, measures that can help ensure market stability in the face of a major supply shock. Unlike power law models that suggest decreasing price volatility over time, one insight from this supply and demand theory approach suggests that any commodity with an absolute hard cap on supply is likely to experience increasing levels of price volatility in the face of declining supply.

By providing a platform for integrating theoretically valid supply and demand models grounded in real-world data and knowledge, our framework provides an important first step towards developing new models that build understanding about how Bitcoin's constrained supply and evolving demand dynamics drive market prices. For parameters that are currently unknown—permanently lost Bitcoin, for instance—new information will continually help refine industry beliefs about the actual number lost, contributing to model development and parameterization refinements. With a supply and demand framework in place, testing alternative functional forms and price determinants will be possible, allowing researchers to identify likely upper and lower bounds to price forecasts.

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Conflicts of Interest: Satoshi Action Education is a 501(c) (3) nonprofit. M.A.R. reports a relationship with Satoshi Action Education that includes consulting or advisory. D.P. reports a relationship with Satoshi Action Education that includes board membership and employment.

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