Datamine: *Proof-of-Burn* Based Platform for Mitigating Volatility of Digital Assets

Datamine Community

August 2022

Abstract

This paper proposes a novel algorithmic solution to managing volatility of digital assets. The dual-token algorithm combines scarcity pricing with the Proof-of-Burn cryptographic mechanism to achieve a low volatility asset for managing risks in crypto denominated portfolios. Key governing principles of the algorithm are validated using regression methods. Forecasting tool for projecting future values of the tokens is described.

1 Introduction

The traditional central bank-based and fiat currency-centered global financial system established aftermath the World War II has exhausted its viability. Loose monetary policies of central banks to stimulate economic growth led to systematic failures, including asset price bubble in early 2000s, the global financial crisis in 2008, and spiraling inflation in 2022. There is a growing consensus among investors and academics that monetary policy is political not technical, further eroding credibility of world's central banks as neutral and unbiased guardians of global economy [14]. Recent developments in blockchain technology have enabled the alternative decentralized finance (DeFi) model based on secure distributed ledgers in which a variety of crypto assets circulate. The DeFi system substitutes for banks and other centralized financial institutions in managing money, financial products, and financial services.

Unlike traditional financial instruments, such as fiat currencies and securities, digital assets, including cryptocurrencies and security tokens, offer fast, secure, reliable, and low cost transactions [7]. Valuations of digital assets, led by two largest cryptocurrencies - Bitcoin (BTC) and Ethereum (ETH) - have greatly increased in the last decade, and their risk-adjusted returns (measured by Sharpe ratio) were on par with or exceeded high-performing traditional assets [9]. A rapidly growing number of investors now have digital assets in their portfolios.

Digital assets' prices and returns have significantly higher volatility than those of fiat currencies, securities, and physical assets, such as gold [3]. This constitutes a major challenge for their widespread adoption. In theory, the volatility problem can be solved by creating efficient portfolios of digital asset classes that balance their risks and returns [11]. Until recently, the main solution to volatility of digital assets has been their collaterization by fiat (e.g., USDT and USDC), other crypto assets (DAI) or physical assets, such as gold (GDX).

Recent innovations in the blockchain industry that led to emergence of algorithmic instruments provide an alternative solution to the volatility problem. Unlike collateralized solutions, algorithmic instruments are backed by an on-chain algorithm that regulates the supply and demand of a digital asset [6]. Performance of algorithmic instruments depends critically on their economic design. This point is well illustrated by the demise of Terra (UST) whose peg to USD collapsed. A number of analyses have attributed the collapse of UST to flawed economic foundations of its key lending protocol, Anchor [6, 12].

This paper proposes a novel algorithmic solution to managing volatility of digital assets. The dual-token algorithm combines the scarcity pricing economic mechanism [15] with the Proof-of-Burn cryptographic mechanism [8], which allows for destroying crypto assets in a verifiable manner. Scarcity pricing mechanism embedded in the DAM token constrains supply of FLUX tokens used for transacting and prevents their unbound inflation leading to large-scale depreciation of its value. The Proof-of-Burn mechanism balances excess supply of FLUX token by offering financial incentives to temporarily withdraw FLUX from circulation. This limits volatility resulting from sharp declines in demand for digital assets akin to those that led to debacle of UST.

It is important to note that *Datamine* algorithm does not result in a stablecoin. Instead, in line with the modern portfolio theory, it's main purpose is to reduce the risk of holding a digital asset portfolio by combining instruments whose returns are correlated but exhibit different degrees of volatility. As the FLUX token is designed as a low volatility asset, users will find it optimal to long it while shorting high volatility digital assets when the market for crypto assets contracts and vice versa. In addition to its economic value as risk-hedging instrument, the *Datamine* algorithm has other intrinsic advantages over other algorithms including strong network security (evidenced by a large number of validators) and integration with other DeFi liquidity pools. When FLUX global liquidity becomes large, FLUX token's volatility and inflation are both expected to decrease to minimum levels, strengthening the rationale for using the FLUX token for conventional financial transactions.

The rest of the paper is structured as follows. The second section describes the formal model outlining economic foundations of the algorithm. The third section demonstrates the results of the regression analysis of key drivers of price and value formation of the DAM and FLUX tokens. The fourth section describes the forecasting tool for projecting future values of the tokens. The final section briefly describes limitations of existing analysis and directions for future research.

2 Economic Structure of the Datamine Ecosystem

Let $n = \Sigma_i$ be the number of unique validators in period t, where i is a unique validator index. In this paper we study equilibrium properties of a large network, which ensures that the market for DAM and FLUX tokens is competitive and can't be manipulated by an individual user. For this assumption to hold, n can't be a small number and the market share of each validator i can't be large [4].

2.1 Scarcity Pricing Mechanism: DAM token

Let M^D be the quantity of Datamine (DAM) tokens. The total of supply of DAM tokens, $\bar{M}^D$, is capped at 16,876,779, so the following inequality always holds:

$$M_t^D = \Sigma_i M_{i,t}^D \leq \bar{M}^D. \tag{1}$$

Inequality (1) implies that once the total of supply of DAM tokens hits its cap $\bar{M}^D$, its supply becomes totally inelastic, and the token value will be entirely determined by growth in uncertain demand consistent with the scarcity pricing principle.

2.2 Proof-of-Burn Mechanism: FLUX token

The DAM token is a digital asset whose primary purpose is to securely produce a stable supply of FLUX utility tokens. Each locked unit i of the DAM token, M^D, conditional on previously burned amount of FLUX Tokens, $M^{F,b}$, at time t yields

$$\Delta M_{i,t}^{F,m} = s \cdot d \cdot M_{i,t}^{D} \cdot \frac{\min\left\{\beta_b, \beta_s \cdot \left(\frac{M_{i,t}^{F,b}/M_{i,t}^{D}}{M_{t}^{F,b}/M_{t}^{D}} + 1\right)\right\}}{\beta_s^2} \cdot \min\left\{\beta_\tau, \frac{\beta_{\tau,s}}{\beta_{\tau,e}} \cdot \Sigma_{\tau=1}^{t} d + \beta_s\right\} \tag{2}$$

FLUX tokens, where

s : FLUX token baseline mint rate per 1 DAM-ETH block fixed at 0.00000001;

d : ETH Blocks per day fixed at 6000

β_b : Burn bonus multiplier base fixed at 100,000

β_τ : Time bonus multiplier base fixed at 30,000

β_s : Ratio scaling factor fixed at 10,000

$\beta_{\tau,s}$: Time bonus scaling factor fixed at 20,000

$\beta_{\tau,e}$: Time bonus exempted DAM lock-in blocks fixed at 161,280.[1]

Equation (2) combines three multipliers governing the supply of FLUX tokens. The baseline multiplier, $s \cdot d$, yields a fixed amount of FLUX tokens per each DAM token that is powering a Validator. The *burn bonus* multiplier described by the second term of equation (2) increases the FLUX token yield proportional to the amount of FLUX tokens burned by an individual Validator relative to the amount of FLUX tokens burned by all Validators. DAM Validators are thus rewarded a faster FLUX mint rate when more of their FLUX tokens are withdrawn from circulation relative to total net FLUX supply (i.e., the difference between FLUX tokens minted and burned). The third term of equation (2) is the *time bonus* multiplier, which increases the FLUX mint rate proportional to the time a DAM token is powering a Validator. Observe that

$$1 \leq \frac{\min\left\{\beta_b, \beta_s \cdot \left(\frac{M_{i,t}^{F,b}/M_{i,t}^{D}}{M_{t}^{F,b}/M_{t}^{D}} + 1\right)\right\}}{\beta_s} \leq 10, \tag{3}$$

and

$$1 \leq \frac{\min\left\{\beta_\tau, \frac{\beta_{\tau,s}}{\beta_{\tau,e}} \cdot d + \beta_s\right\}}{\beta_s} \leq 3. \tag{4}$$

That is each point of time the burn bonus multiplier can't exceed 10 times of a baseline FLUX mint rate and the time bonus multiplier can't exceed 3 times of a baseline FLUX mint rate. The burn bonus multiplier leverages the Proof-of-Burn mechanism to provide economic incentives for reducing FLUX price volatility. If the FLUX token price falls temporarily below its long-run

[1] Failsafe parameter, which doesn't have economic justification.

equilibrium value, Validators have incentives to burn the excess supply of FLUX tokens at low cost, leading to a rebound in FLUX price and the value of their FLUX portfolio. Their losses from burning FLUX tokens are also offset by realized future gains from an increased FLUX mint rate. Formally, at any period t the value creation multiplier of the FLUX token is given by

$$VCM_{F,t} = \frac{\sum_t M_t^F}{\sum_t M_t^{F,b}} \tag{5}$$

The time bonus multiplier also lowers FLUX price volatility as it lowers the velocity of FLUX tokens in circulation.

2.3 Liquidity Pools

DAM and FLUX tokens are traded on DeFi exchanges, such as Uniswap V3 [1]. DeFi exchanges offer users incentives to add liquidity to their trading pools by rewarding providers with the fees generated when other users trade with those pools. That is r percent of all trade volume in the liquidity pool, V^p, is distributed proportionally to all liquidity providers. The return on M^p DAM or FLUX tokens in the pool is thus given by

$$(1 + r_I) \cdot \frac{M_{i,t-1}^{I,p}}{M_{t-1}^{I,p}} \cdot V_{I,p},\ I = \{D, F\}.^2 \tag{6}$$

2.4 Token Supply

The following equations describe token supply, where M^F denotes quantity of FLUX tokens in free circulation and Δ is the time difference operator:

$$M_{i,t}^D = M_{i,t-1}^D + \Delta M_{i,t}^D + (\Delta M_{i,t}^{D,p} - \Delta M_{i,t}^{p,D}) + (1 + r_D) \cdot \frac{M_{i,t-1}^{D,p}}{M_{t-1}^{D,p}} \cdot V_{D,p} \tag{7}$$

$$\begin{aligned} M_{i,t}^F = M_{i,t-1}^F + \Delta M_{i,t}^{F,m} - \Delta M_{i,t}^{F,b} - (\Delta M_{i,t}^{F,p} - \Delta M_{i,t}^{p,F}) \\ +(1 + r_F) \cdot \frac{M_{i,t-1}^{F,p}}{M_{t-1}^{F,p}} \cdot V_{F,p} \end{aligned} \tag{8}$$

$$M_{i,t}^{j,p} = M_{i,t-1}^{j,p} + \Delta M_{i,t}^{j,p} - \Delta M_{i,t}^{p,j}\ j = D, F. \tag{9}$$

[2] This formula doesn't account for impermanent risk loss resulting from differences in cryptoasset prices compared to when these assets were deposited in the pool. For more information on impermanent risk loss please refer to [10].

Equation (7) states that the value of total DAM powering Validators, M^D, in a given period equals their value in the previous period, and the sum of the value of newly locked-in DAM tokens, $\Delta M^{D,m}$, the difference in value of DAM tokens added and removed from a liquidity pool, $\Delta M_{i,t}^{D,p} - \Delta M_{i,t}^{p,D}$, and the return on the DAM liquidity pool shown by equation (6). Equation (8) states that the value of FLUX tokens in circulation in a given period equals their value in the previous period, the difference in FLUX minted (see equation 2) and burned, the difference in value of FLUX tokens added and removed from a liquidity pool, and the return on the FLUX liquidity pool. Equation (9) tracks the value of DAM and FLUX tokens in their liquidity pools, based on their values in the previous period, and net inflows in the liquidity pool.

2.5 Token Demand

The demand for the DAM token is driven primarily by the demand for global crypto assets and tracks the demand for larger benchmarks such as BTC and ETH. When the market for crypto assets grows users will find it optimal to long the DAM token, and vice versa. It is also driven by the size and the rate of return of DAM liquidity pools. When liquidity in the pool is diminished, the demand for the DAM token may increase to take advantage of the greater relative share of revenues from future DAM market transactions. Finally, the demand for DAM tokens depends on transaction cost on Ethereum blockchain, also known as "gas" fees, which in turn, depend on Ethereum network congestion.[3] Formally, we can represent the demand function for DAM tokens as

$$Q^D = \mathcal{D}(\mu_E, r_D, M^{D,p}/M^D, g) \tag{10}$$

where Q^D is the DAM token demand, μ_E : benchmark crypto asset price, r_D and $M^{D,p}/M^D$ are, respectively, the rate of return and the relative size of the DAM liquidity pool, g are ETH gas fees, and $\mathcal{D}$ is the demand function operator.

The demand for the FLUX token is driven by similar factors as for the DAM token *and* the volatility of larger crypto assets. Higher volatility of BTC or ETH price creates additional demand for FLUX tokens because users can arbitrage their price swings. As FLUX token price tracks benchmarks, when the BTC or

[3] Datamine also operates on Arbitrum blockchain, a layer-2 solution that supports smart contracts without the limitations of scalability such as Ethereum and has arguably lower transactions costs. We don't analyze Arbitrum transactions in this paper due to data limitations.

ETH price declines its price also falls. This creates incentives for buying and burning FLUX tokens, accumulating FLUX tokens at faster rate and selling the premium when the benchmark price recovers. Formally, we can represent the demand function for FLUX tokens as

$$Q^F = \mathcal{D}(\mu_E, \sigma_E, r_F, M^{F,p}/M^F, g) \tag{11}$$

where σ_E is the benchmark price volatility and other notations follow closely equation (10).

2.6 Tokenomics of the Datamine Ecosystem

For simplicity, we assume that (i) DAM and FLUX token velocities in their liquidity pools are constant and thus have no effect on price movements and (ii) market participants don't know future gas fees and use average gas fees as a proxy for future gas fees.[4]

Then using the results from sections 2.4 and 2.5 we can derive the equilibrium prices of DAM and FLUX tokens as

$$p^D = \mathcal{F}(M^D, Q^D) \tag{12}$$

and

$$p^F = \mathcal{F}(M^F, Q^F) \tag{13}$$

where $\mathcal{F}$ is a contractor function operator.

We can now identify key trade-offs faced by the network participants. A DAM token holder can choose to become a Validator and validate new FLUX tokens or add them to a DAM liquidity pool. The choice between these two decisions per marginal unit of DAM is defined by the following margin:

$$\left(p^D_{t-1} - g_t\right) \left((1 + r_D) \cdot \frac{M^{D,p}_{i,t-1}}{M^{D,p}_{t-1}} \cdot V_{D,p} \right) = \left(p^F_t - g_t\right) \Delta M^{F,m}_{i,t} \tag{14}$$

The left hand side of equation (14) is the opportunity cost of becoming a DAM Validator (i.e., the marginal gain of adding tokens to DAM liquidity pool), whereas the right hand side of this equation is the opportunity cost of adding DAM tokens to liquidity pool (i.e., the marginal gain of validating new FLUX

[4] Relaxing either assumption complicates derivations without changing main results of the paper.

per marginal DAM unit locked). Observe that network participants may find it optimal to pursue neither if ETH gas fees exceed the marginal values of validating new FLUX tokens or adding to liquidity pool.

A FLUX token holder can choose to burn FLUX tokens in exchange for an increased FLUX generation rate or add them to a FLUX liquidity pool. The choice between these two decisions per marginal unit of FLUX is defined by the following margin:

$$\left(p^F_{t-1} - g_t\right)\left((1 + r_F) \cdot \frac{M^{F,p}_{i,t-1}}{M^{F,p}_{t-1}} \cdot V_{F,p} + \Delta M^{F,b}_{i,t}\right) =$$

$$\left(p^F_t - g_t\right)\left(\min\left\{\beta_b, \beta_s \cdot \left(\frac{M^{F,b}_{i,t}/M^D_{i,t}}{M^{F,b}_t/M^D_t} + 1\right)\right\} + \Delta M^{F,p}_{i,t}\right) \tag{15}$$

The left hand side of equation (15) is the opportunity cost of burning FLUX tokens (i.e., the gain of adding a marginal token to a FLUX liquidity pool and the value of a marginal token burnt), whereas the right hand side is the opportunity cost of adding FLUX tokens to liquidity pool (i.e., the marginal future gain from burning FLUX due to higher burning bonus multiplier and the value of a marginal token added to the liquidity pool).

3 Regression Analysis of DAM and FLUX

This section shows the regression analysis of DAM and FLUX token supply and price formation described above. The data sample covers the periods of November 2020 to April 2022 for the FLUX token and May 2021 to April 2022 for the DAM token and FLUX liquidity pools. The earlier data are omitted due to unsettled market characterized by extreme volatility of both tokens.

Figure 1 shows evolution of DAM and FLUX token prices denominated in US dollars (USD). DAM token price exhibits low volatility fluctuating between \$0.1 and \$0.15 per token over most of the data sample. There are two short-term spikes in the DAM token value driven by *ad hoc* events after which its value reverses back to its mean. The FLUX token price is more volatile, exhibiting greater fluctuations, but is also mean-reverting to its average of \$0.5. Sharp fluctuations in the FLUX token price are largely driven by its relatively small market size and is expected to decline once the network expands and the market for FLUX tokens saturates.

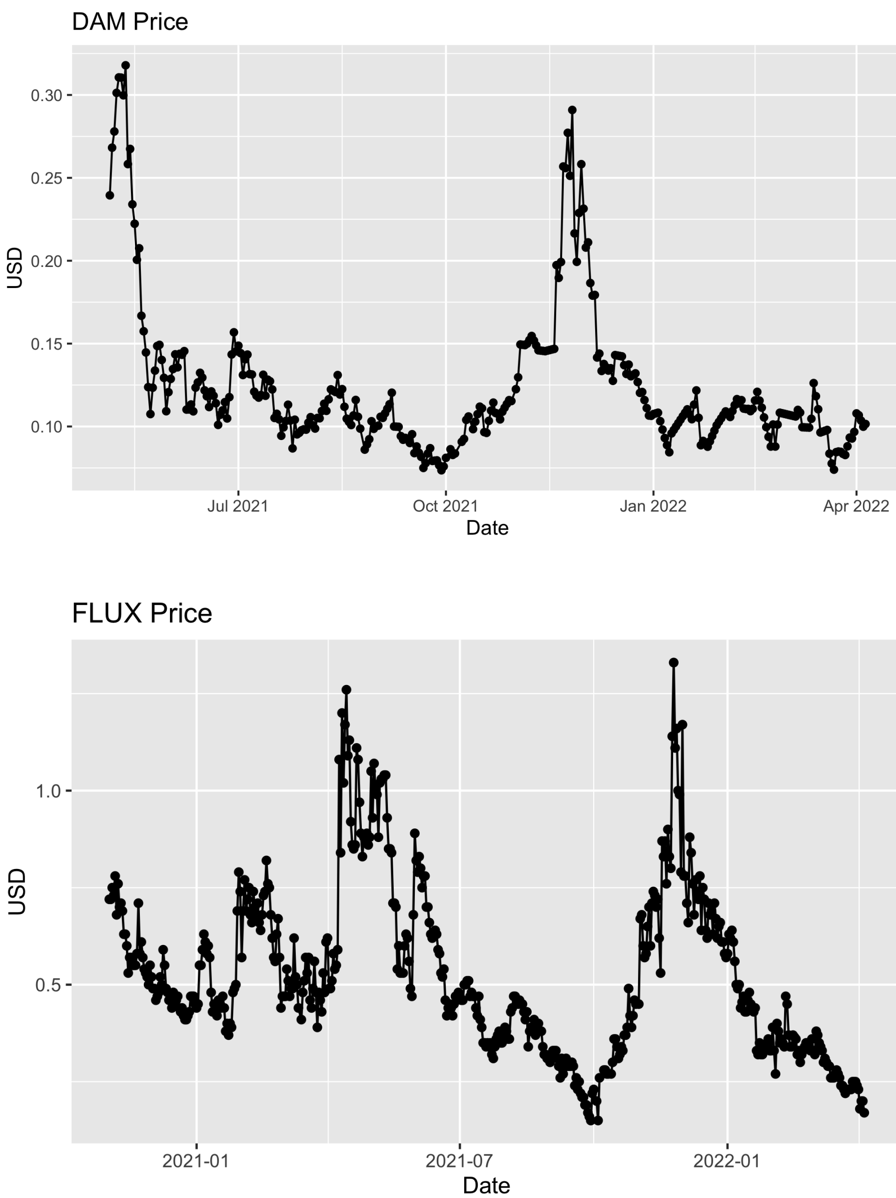

Figure 1: DAM and FLUX token price series

Table 1: Determinants of Token Prices

	Dependent variable:	
	DAM/USD	FLUX/USD
	(1)	(2)
Gas Fees	0.11***	0.56***
	(0.04)	(0.18)
ETH/USD, log	0.42***	2.81***
	(0.04)	(0.47)
ETH/USD, log squared	0.24***	1.41***
	(0.03)	(0.23)
Total DAM Validators, log	−0.40***	
	(0.03)	
Total DAM Validators, log squared	0.32***	
	(0.03)	
Total FLUX Supply, log		−0.25***
		(0.04)
ETH Volatility Index		0.11***
		(0.04)
Constant	0.11***	0.22***
	(0.004)	(0.04)
Observations	328	509
Adjusted R^2	0.57	0.22
F Statistic	88.82***	29.94***

Note: Variables are scaled to numeraire units. *p<0.1; **p<0.05; ***p<0.01

Table 1 shows results of a regression analysis of DAM and FLUX token prices based on key factors identified in the previous section of this paper.[5] On demand side, the price of both tokens increases with benchmark ETH price, and the price of the FLUX token increases with the ETH Volatility Index, confirming the theoretical results from the previous section. On supply side, the price of both tokens increases with ETH gas fees, reflecting higher transactions costs.

Consistent with the quantity theory of money [5], the price of the FLUX token decreases linearly as the supply of the FLUX token increases. The price of the DAM token responds non-linearly to expansion of DAM validators, first declining and then increasing as the number of DAM validators grows. This result can be explained by the scarcity principle. First, the DAM token price declines with excess supply caused by expansion of DAM token validators. However, when the number of DAM validators approaches its maximum limit, DAM supply becomes tight and the DAM token price increases. All results are statistically significant at the 1% confidence level.

Figures 2 and 3 show the results of testing estimated regression coefficients stability over time using rolling regression approach. Specifically, we estimate regressions shown in Table 1 across a fixed windows of 30 days and then iterate forward regressions with that window across the data set. Estimated coefficients for the DAM token regression are stable across time with an exception of the period of December 2021 to February 2022, caused by a major volatility spike in DAM price in November 2021. Estimated coefficients for the FLUX token show major instability around the same period, and are also less stable generally. Nonetheless, they all mean revert to their expected values, supporting confidence in the regression analysis' results.

Table 2 takes one step further by showing results of regression analysis of the economic mechanisms governing FLUX token supply and demand. The first column of Table 2 shows that the amount of total FLUX tokens minted depends negatively on transactions costs (i,e., ETH gas fees) and positively on the number of total DAM validators. The second column of Table 2 shows that FLUX value creation multiplier (see equation 5) declines in ETH gas fees (which lower FLUX mints) and volatility index (which increases FLUX burns) but increases with ETH benchmark price (which leads to higher demand for the FLUX token). Finally, the third column of Table 2 shows that the size of FLUX liquidity pool declines with value creation multiplier, confirming the

[5] The polynomial order of each factor was determined by shrinking methods using LASSO regression maximizing goodness of fit [13].

key trade-off faced by Datamine network participants of burning newly minted FLUX tokens versus adding them to FLUX liquidity pools. Again, all results are consistent with the analysis in section 2 and statistically significant at the 1% confidence level.

Table 2: Determinants of FLUX Token Supply

	Dependent variable:		
	Total FLUX Minted	Value Creation Multiplier	FLUX Liquidity Pool
	(1)	(2)	(3)
Gas Fees	-2.12^{***}	-0.36^{***}	
	(0.44)	(0.07)	
ETH/USD		0.07^{***}	
		(0.003)	
Total DAM Validators	0.52^{***}		
	(0.04)		
ETH Volatility Index		-0.04^{***}	
		(0.01)	
Value Creation Multiplier			-0.40^{***}
			(0.02)
Constant	-4.88^{***}	1.53^{***}	0.80^{***}
	(0.45)	(0.02)	(0.03)
Observations	509	509	325
Adjusted R^2	0.30	0.51	0.56
F Statistic	108.49^{***}	175.94^{***}	406.56^{***}

Note: Variables are scaled to numeraire units. *p<0.1; **p<0.05; ***p<0.01

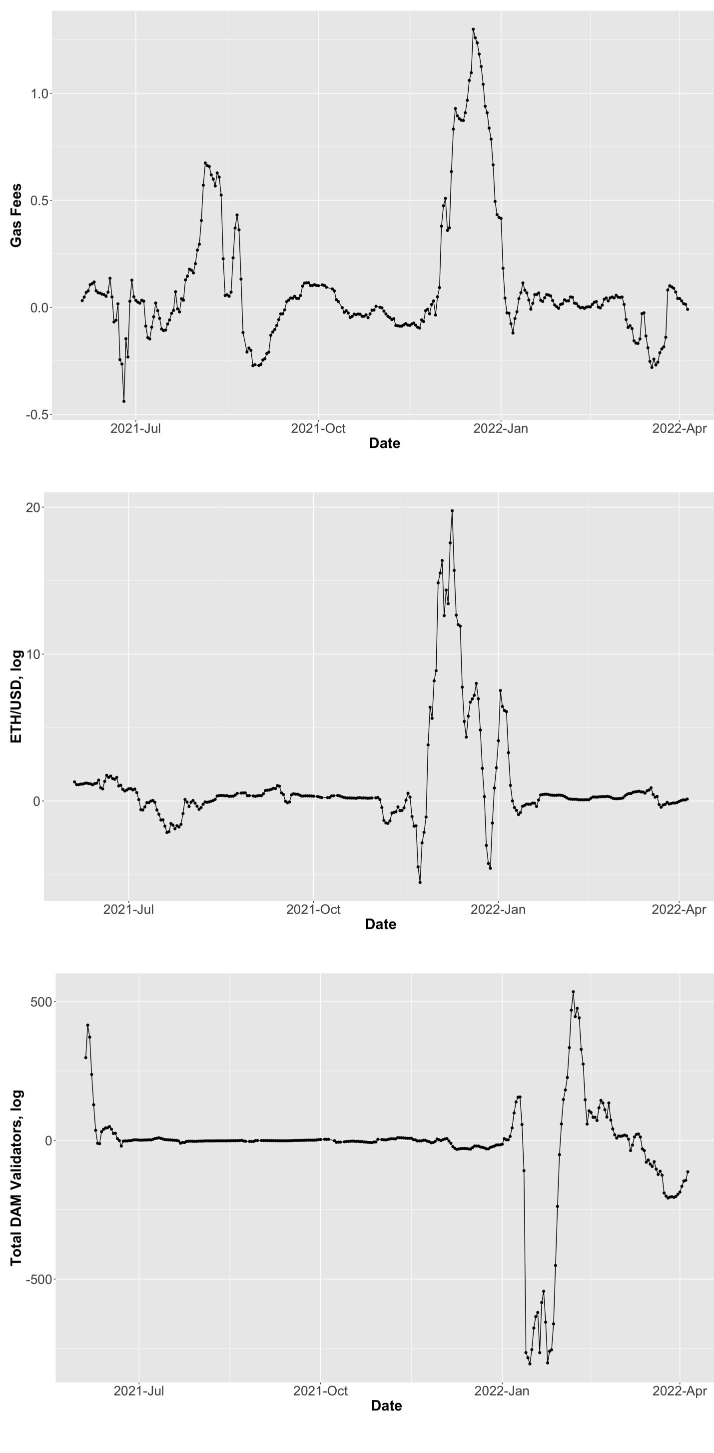

Figure 2: Rolling Regression Coefficients: DAM Prices

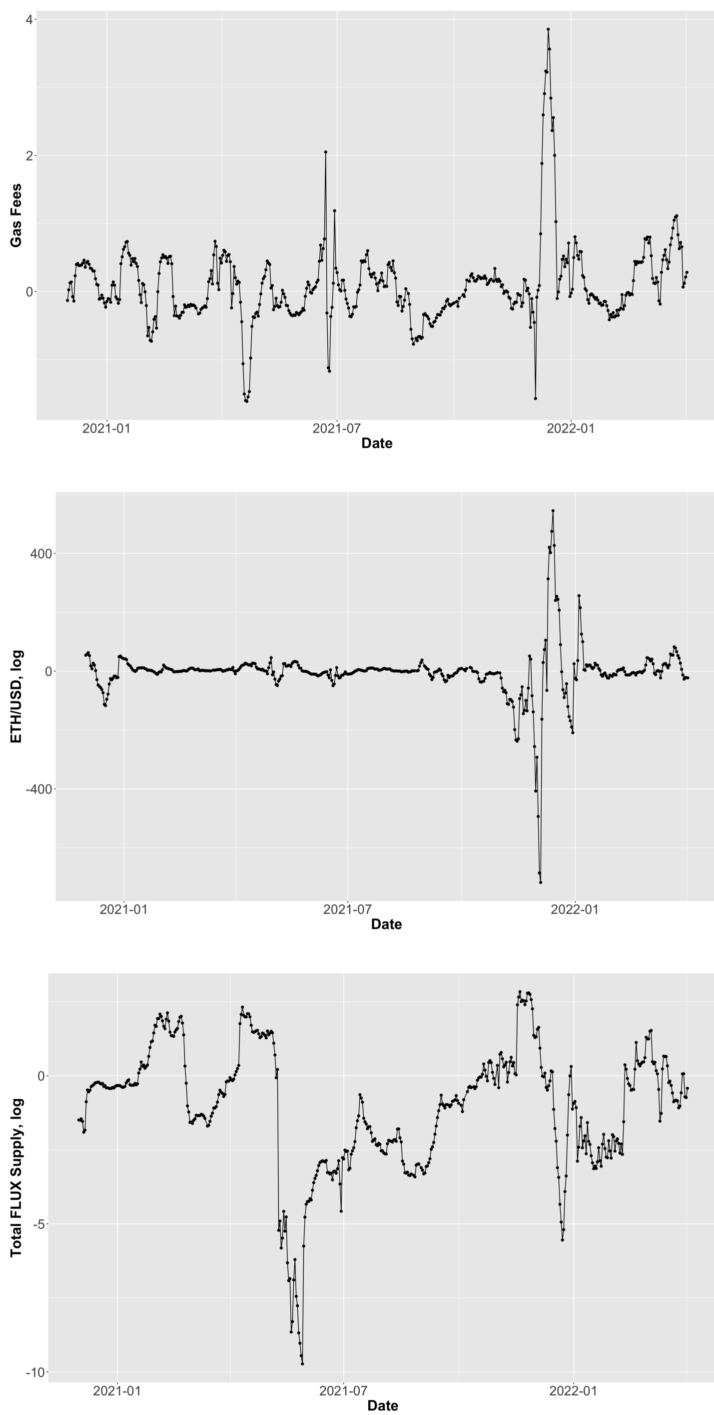

Figure 3: Rolling Regression Coefficients: FLUX Prices

4 Datamine Forecasting Tool

Datamine forecasting tool develops projections for DAM and FLUX token supply and prices using a combination of calibration and regression modeling methods. Inputs include current ETH price, ETH price growth projections, historical ETH volatility, estimated gas fees, and DAM total validators. The tool has two options: deterministic where all projections are assumed to be certain (i.e., only a single future trajectory is available for each model input), and stochastic, where some model inputs (e.g., ETH price and volatility) are drawn from a known distribution and can take different values each period. The stochastic model can be used to construct confidence intervals for the deterministic model outputs. All model equations are shown in appendix.

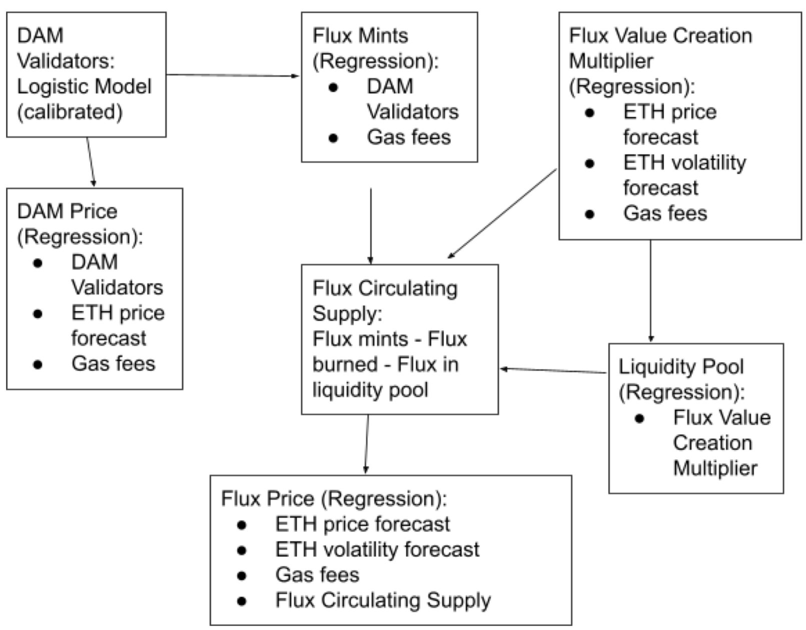

Figure 4: Forecast Tool Structure

The model structure is shown in Figure 4. The tool first forecasts future DAM validator growth based on the logistic model calibrated to match DAM validator nodes' historical evolution. DAM validator forecasts are used in regression models to estimate projections for DAM token prices and total FLUX token mints. Another regression model estimates the projections for FLUX value creation multiplier. FLUX value creation multiplier projections are combined with estimated total FLUX token mints to infer total FLUX token burns. It is also used in another regression model to determine the margin at which the network participant breaks even by adding FLUX to the liquidity pool and the liquidity pool size. Estimates of total FLUX token minted, burned, and added to liquidity pool are used for calculating projections of FLUX token circulating supply. Finally, estimates of FLUX circulating supply, combined with ETH price and volatility forecasts are used in the final regression to determine the FLUX token price forecast.

5 Limitations and Directions for Future Research

The main limitations of current analysis are a relatively short duration of data series and the small market size of the network. As network expands it becomes more resilient to short-term volatility spikes and longer data series help establishing more credible estimates used for both inference and forecasts. The analysis in this paper should be replicated in the future using a large sample of DAM validators and network transactions. When data improves, the analysis can be replicated using more sophisticated time-series analysis methods, such as e.g., multivariate GARCH models [2].

References

[1] Adams, Hayden, Noah Zinsmeister, Moody Salem, River Keefer, and Dan Robinson, "Uniswap v3 core" in: `https://uniswap.org/whitepaper-v3.pdf`; 2021

[2] Bauwens, Luc, Sebastien Laurent, and Jeroen VK Rombouts, "Multivariate GARCH Models: a Survey" in: Journal of Applied Econometrics. 21(1): 79−109; 2006

[3] Caginalp, Carey, and Gunduz Caginalp, "Opinion: Valuation, Liquidity Price, and Stability of Cryptocurrencies" in: Proceedings of the National Academy of Sciences 115: 1131−34; 2018

[4] Deuflhard, Florian, and Heller, C.-Philipp, "Antitrust Economics of Cryptocurrency Mining" in: SSRN: https://ssrn.com/abstract=3917012; 2021

[5] Friedman, Milton, "Quantity Theory of Money" in: The New Palgrave: A Dictionary of Economics, 4, page 15; 2018

[6] Gen¸ Ekin, "Algorithmic Stablecoins: What They Are and How They Can Go Terribly Wrong" in: Coindesk Crypto Explainer+: https://www.coindesk.com/learn/algorithmic-stablecoins-what-they-are-and-how-they-can-go-terribly-wrong/; 2022

[7] Hileman, Garrick, and Michel Rauchs, "Global Cryptocurrency Benchmarking Study" in: Cambridge Centre for Alternative Finance. Cambridge: Cambridge Judge Business School, University of Cambridge; 2017

[8] Karantias, Kostis, Kiayias, Aggelos and Dionysis Zindros, "Proof of Burn" in: IOHK Paper: https://https://eprint.iacr.org/2019/1096.pdf; 2019

[9] Liu, Yukun, and Aleh Tsyvinski, "Risks and Returns of Cryptocurrency" in: The Review of Financial Studies. 34.6: 2689−2727; 2021

[10] Loesch, Stefan, Nate Hindman, Mark B. Richardson, and Nicholas Welch, "Impermanent Loss in Uniswap v3" in: ArXiv preprint arXiv:2111.09192; 2021

[11] Markowitz, Harry M., "Portfolio Selection" in: The Journal of Finance. 7(1): 77−91; 1952

[12] Onchain Wizard, "Understanding the Mechanics of the Rise & Fall of LUNA/UST" in: Onchain Wizard's Newsletter: https://onchainwizard.substack.com/p/onchain-wizard-understanding-the; 2022

[13] Tibshirani, Robert, "Regression Shrinkage and Selection via the LASSO." in: Journal of the Royal Statistical Society: Series B (Methodological). 58(1): 267-288; 1996

[14] Tooze, Adam, "The Death of the Central Bank Myth" in: Foreign Policy: https://foreignpolicy.com/2020/05/13/european-central-bank-myth-monetary-policy-german-court-ruling; 2020

[15] Working, Holbrook, “The Theory of Price of Storage” in: The American Economic Review. 39(6): 1254-1262; 1949

Appendix

Forecast Model equations

1. ETH price forecast: $ETH/USD_t = ETH/USD_1 \cdot (1+k)^t$, where k is ETH appreciation rate calculated based on historical data.

2. Total DAM validators forecast: $DAM_t = \frac{DAM_T \cdot DAM_1 \cdot e^{rt}}{DAM_T + DAM_1 \cdot (e^{rt}-1)}$, where r is the logistic growth rate to be calibrated.

3. DAM price forecast: $P_t^{DAM} = \beta_0 + \beta_1\{gasfees\}_t + \beta_2 \log\{ETH/USD\}_t + \beta_3 \log\{ETH/USD\}_t^2 + \beta_4 \log\{DAM\}_t + \beta_5 \log\{DAM\}_t^2 + \varepsilon_t$, where ε is error term.

4. FLUX minted forecast: $FLUX_t^m = \beta_0 + \beta_1\{gas\ fees\} + \beta_2\{DAM\}_t + \varepsilon_t$

5. FLUX value creation multiplier forecast: $VCM_t = \beta_0 + \beta_1\{gas\ fees\}_t + \beta_2\{ETH/USD\}_t + \beta_3\{ETH\ Volatility\}_t + \varepsilon_t$

6. FLUX burned forecast: $FLUX_t^B = FLUX_t^m / VCM_t$

7. FLUX in liquidity pool forecast: $FLUX_t^l = \beta_0 + \beta_1\{VCM\}_t + \varepsilon_t$

8. FLUX in circulation supply forecast: $FLUX_t^s = FLUX_t^m - FLUX_t^B - FLUX_t^l$

9. FLUX price forecast: $P_t^{FLUX} = \beta_0 + \beta_1\{gasfees\}_t + \beta_2 \log\{ETH/USD\}_t + \beta_3 log\{ETH/USD\}_t^2 + \beta_4\{FLUX^s\}_t + \beta_5\{ETH\ Volatility\}_t + \varepsilon_t$