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THE TOKENOMICS OF STAKING

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ABSTRACT

Tokens offer convenience in digital networks and earn rewards when staked for consensus generation or economic activities. In our continuous-time model, agents dynamically allocate wealth over on-platform transactions and staking. Aggregate staking ratio crucially shapes platform productivity, grows userbase, and links staking to endogenous reward rates and price dynamics. Transaction fees, token issuance, and user heterogeneity all affect platform lifecycle. Empirical findings support the theoretical predictions:(i) correlation between staking ratio and reward rate is cross-sectionally positive, but time-series-wise negative; (ii) staking ratios positively predict excess returns; (iii) the convenience wedge generates UIP violations and significant crypto carry premia.

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1 Introduction

The past decade witnessed an explosive growth in blockchain-based platforms and cryptocurrencies, which totaled 3.5 trillion USD in market capitalization, and a rising interest in Decentralized Finance (DeFi) (Harvey, Ramachandran, and Santoro, 2021), which entails over 210 billion USD worth of assets locked in DeFi protocols, all as of Jan 2025. Platform tokens derive value by enabling users to complete economic transactions and hold stakes in the ecosystem, making them a hybrid of money and investible assets. The recent prevalence of token staking (value locking and yield farming, see, e.g., Augustin, Chen-Zhang, and Shin, 2022) for higher-layer DeFi innovations as well as for base layer consensus formation (e.g., through Proof-of-Stake, PoS, as discussed in John, Rivera, and Saleh, 2022) further calls for a unified framework to understand the use of tokens as transaction media, investment assets, and deposit/collateral-like instruments. To this end, we relate various functions tokens provide (e.g., transaction convenience and financial rewards through holding and staking) to token pricing, both theoretically and empirically, with endogenous adoption and agent heterogeneity.

Specifically, we build a continuous-time model of an economy with a tokenized digital network, where agents optimally conduct transactions on a platform subject to both platform productivity and external shocks, and stake tokens to earn rewards from both newly minted tokens and fees. We discover the aggregate staking ratio—the number of staked tokens over the total token supply—to be key in determining equilibrium reward rates and token prices. The convenience wedge between onchain and offchain assets also drives the violation of uncovered interest rate parity (UIP) and predicts profitable carry trades. We show staking facilitates redistribution from users to stakers, as in an inflation tax, and further discuss the platform's ability to manage its lifecycle by manipulating staking incentives (through fee and emission designs) while balancing network scale and staking contribution from potentially heterogeneous users.

Empirical evidence from a dataset covering all major stakable tokens also corroborates the model predictions. In particular, staking ratio positively correlates to both reward rates and price appreciation in the cross section, compensating the convenience loss of staking. To our knowledge, this study is the earliest and most comprehensive investigation into the effects of staking on token pricing, and the violations of UIP (and the resulting carry premia) for stakable tokens, which dominate the cryptocurrency market excluding Bitcoin. Our study also provides insights for cryptocurrency traders, platform designers, and users who need to discern between viable staking programs from scams.

We start by conceptually clarifying two broad categories of staking: those related to pan-PoS consensus protocols and those in higher-layer (decentralized) applications.[1] Fundamentally, blockchain functions to generate a relatively decentralized consensus record of system states to enable economic interactions such as value or information exchanges (e.g., Cong and He, 2019). PoS consensus protocols have gained popularity with major market players such as Ethereum adopting them. Under PoS, agents stake native tokens to compete for the opportunity to record transactions, execute smart contracts, append blocks, etc., to earn block rewards and fees (e.g., Saleh, 2021; Kogan, Fanti, and Viswanath, 2021; Jermann, 2023). Meanwhile, various staking programs have become popular means for incentivizing desirable behavior in higher layer applications, escrowing a balance of tokens under custody in a smart contract or deploying them to enable network economic functionalities with stakers earning staking rewards (e.g., Augustin, Chen-Zhang, and Shin, 2022).

Our model applies to both categories and captures several distinguishing features of staking economies. First, such tokens are used on platforms that support specific economic transactions or broader use in onchain-based projects. This generates utility flows in, e.g., transaction convenience discussed in (Cong, Li, and Wang, 2021b; Biais et al., 2020). Second, the rate of staking rewards that an agent earns is influenced by other agents' behavior in aggregate, but individuals take it as given when making decisions.[2] Third, staking participation can influence the platform's development, e.g., by improving the efficiency and security of services, which enriches the agents' roles within the platform, although it is not a necessary feature in all the projects. In addition, the framework also applies to the recently growing restaking activities once we allow a general form of the convenience loss of staking.

We solve for the Markov equilibrium of the staking economy, which is characterized by three state variables: platform productivity, token supply, and external demand shocks. In equilibrium, the staking reward rate solves a fixed-point problem, while the token price dynamics are endogenously determined by a partial differential equation (PDE). Comparing the pricing formula

[1]The two are not mutually exclusive. Solana, for example, uses both PoS and DeFi staking. The classification we use follows mainstream cryptocurrency data aggregators such as CoinMarketCap. Even on non-blockchain-based or centralized platforms, various programs that involve escrows or crowd funds can be analyzed as a form of business-layer staking through the lens of our framework.

[2]Polkadot (DOT) constitutes an example: the reward rate for validators is determined by the current aggregate staking ratio. The fewer DOTs are staked, the higher the yield is for a planned amount of reward.

to the Black-Merton-Scholes PDE as well as the benchmark token pricing formula in Cong, Li, and Wang (2021b), we highlight how staking endogenously influences token price dynamics with rich implications discussed in detail next.

Using economic intuition to simplify the PDE into an ordinary differential equation with a unique solution subject to two intuitive boundary conditions with respect to platform productivity, we show that the staking ratio proves crucial for token pricing and reward rate determination in equilibrium. Importantly, a higher staking ratio predicts greater token price appreciation due to two key forces. First, an *adoption effect* arises from the joint determination of the staking ratio and expected price appreciation. A higher productivity level attracts greater adoption, which in turn limits future inflows, thereby reducing expected price appreciation. Simultaneously, higher productivity increases the convenience of transactions relative to the benefits of staking, leading to a lower staking ratio. As a result, the staking ratio is positively correlated with price appreciation, which is further amplified by the network externality of the active user base. Moreover, a *feedback effect* arises from the contribution of staking to the growth of platform productivity, which accelerates future adoption and is therefore associated with a higher price drift. These two forces render the staking ratio as a key predictor for token price dynamics, partially justifying the wide adoption by practitioners of the heuristic metric of Total Value Locked (TVL). A higher staking ratio links increased staking reward rates to higher expected price appreciation, driving a convenience wedge between staked tokens and numéraire that violates the Uncovered Interest Parity (UIP). In particular, the convenience wedge is highly sensitive to changes in the staking ratio, suggesting the potential for both staking-ratio-based and crypto carry trading strategies.

We further discuss the platform's ability to manage its lifecycle by adjusting staking incentives. In practice, platforms can set fee policies, and since transaction fees act as a direct cash flow from users to stakers (validators), different fee structures reflect the platform's priorities—balancing the stabilization of its active user base and the acceleration of productivity growth, particularly in its early stages. Token issuance serves a similar role as a redistribution mechanism while affecting the so-called "inflation." Supply increase effectively functions as a tax, providing a powerful policy tool, especially when the platform reaches a mature stage when transactions are less costly and transaction fees have a diminished impact. In addition, we examine the staking economy under user heterogeneity. As the platform expands, an endogenous division of labor among participants is likely to emerge: retail investors increasingly function as pure on-platform users, while validation operations become concentrated among wealthier agents.

We summarize the three main sets of model implications: First, the staking reward is positively related to the staking ratio. While more staking reduces the reward rate for any given reward quantity, more rewards incentivizes more staking, simultaneously yielding a higher staking ratio and a higher staking reward rate in equilibrium. Second, expected price appreciation increases with the aggregate staking ratio, as detailed above. Third, there are generally predictable excess returns to staking over holding the numéraire. The model thus implies that UIP fails for stakable tokens, and further profitable crypto carry trades. Because the reward rate mechanically decreases with a greater staking ratio, carry predicts lower excess returns in the time series than in the cross-section.

We test these model predictions empirically and find corroborating evidence in a comprehensive dataset covering all major stakable tokens (66 tokens from *StakingRewards* spanning July 2018 to November 2022). We first document that a 10-percentage-points increase in the aggregate reward ratio (e.g., from 10% to 20%) is associated with a 7.79-percentage-point higher staking ratio on average. Moreover, the reward rate has a predictable effect on changes in the staking ratio, with a one percentage point increase in the previous week rate increasing the staking ratio in the following week by about 0.026 percentage points. This property is robust to adding both two-way fixed effect and control variables including market cap and token return volatility. However, its significance decreases with longer time intervals, reflecting to some extent the mechanical downward adjustment of the reward rate when more tokens are staked (because the same staking rewards have to be divided among more staked tokens).

We next verify that a larger staking ratio indeed predicts greater future token price appreciation. When the staking ratio increases by one percentage point, the corresponding token price appreciates by 6.6 basis points in the following week. Considering that the variation of staking ratio is often large, especially in the cross-section, this effect is relevant for investments. Crypto market and size factors do not explain the predictive power of staking ratio, which is more related to market liquidity and depth, and reflects the fact that tokens are commodity-like.[3] Staking reduces the supply of liquid cryptocurrencies, and hence pushes up token prices and convenience yields of tokens. This resembles how using commodities as collateral increases the spot price and the convenience yield of the underlying commodities (Tang and Zhu, 2016).

Finally, following the international finance literature, we test if "interest rate" (i.e., reward

[3]Commodities Futures Trading Commission (CFTC) regards cryptocurrencies as commodities, see, e.g., https://www.cftc.gov/sites/default/files/2019-12/oceo_bitcoinbasics0218.pdf.

rate) predicts "currency excess returns" (i.e., token excess return). We find that UIP is indeed violated. We construct a carry trade strategy that goes long high-carry crypto assets and short low-carry assets, yielding an annualized Sharpe ratio of 1.60 with weekly rebalancing. Crypto carry predicts excess returns almost one-for-one in the cross-section, with a reduced albeit significant effect in the time series. Intuitively, higher reward rates attract more staking, which persists over the locked period, reducing the reward rates going forward and thus total expected returns, just as our model implies.

Literature. Our study adds to the literature on blockchain economics and cryptocurrency markets.[4] In particular, we build on the tokenomics framework of Cong, Li, and Wang (2021b) and Cong, Li, and Wang (2021a) to add to emerging studies on Proof-of-Stake protocols (e.g., Fanti, Kogan, and Viswanath, 2021; Saleh, 2021; Benhaim, Falk, and Tsoukalas, 2021) and debates on the environmental and scalability issues associated with Proof-of-Work (PoW) protocols (e.g., Cong, He, and Li, 2021; Hinzen, John, and Saleh, 2019). We also complement the emerging literature on DeFi (e.g., Park, 2021; Cong et al., 2022; Li et al., 2022) by providing a framework for analyzing one of the most prevalent forms of DeFi activity.

The most closely related paper to ours is John, Rivera, and Saleh (2022) which theoretically examines native PoS crypto assets that serve primarily as investment vehicles, whereas we focus on the platform tokens with a combination of transaction usage and investment function. While both studies demonstrate that the equilibrium staking ratio increases in staking rewards, John, Rivera, and Saleh (2022) find that staked asset value can exhibit a non-monotonic relationship with block rewards and cause redistribution across agents with divergent trading horizons. We complement this by endogenizing adopters' contribution to the platform, as well as considering DeFi staking in addition to the PoS consensus and discussing potentially heterogeneous staking preferences. Also closely related is Jermann (2023) who develops a macrofinance model accounting for both the Ethereum EIP-1559 fee mechanism and its new PoS design, while quantitatively

[4]Existing studies mostly examine issues related to consensus algorithms (Biais et al., 2019; Saleh, 2021), cryptocurrency mining (e.g., Cong, He, and Li, 2021; Lehar and Parlour, 2020), scalability (e.g., Abadi and Brunnermeier, 2018; John, Rivera, and Saleh, 2020), fee designs Easley, O'Hara, and Basu (2019); Basu et al. (2019); Huberman, Leshno, and Moallemi (2021), DeFi (e.g., Harvey, Ramachandran, and Santoro, 2021; Capponi and Jia, 2021), ICOs (e.g., Lyandres, Palazzo, and Rabetti, 2019; Howell, Niessner, and Yermack, 2020), pricing of crypto assets (e.g., Liu, Tsyvinski, and Wu, 2019; Cong et al., 2021a; Prat, Danos, and Marcassa, 2019), manipulation and regulation (e.g., Griffin and Shams, 2020; Li, Shin, and Wang, 2021; Cong et al., 2021b, 2023), or digital currencies (e.g., Gans, Halaburda et al., 2015; Bech and Garratt, 2017; Chiu et al., 2019; Cong and Mayer, 2021).

estimating the long-run staking ratio of ETH and the implied money supply. While both studies pin down equilibrium staking considering platform usage value relative to staking benefits, we endogenize the platform productivity process whereas Jermann (2023) endogenizes the token supply. Consequently, our focus is on token pricing instead of monetary policy. Fanti, Kogan, and Viswanath (2021) is the earliest to develop a cash-flow-based valuation framework of PoS cryptocurrencies to understand how the liquidity of validators' holdings, token valuation, and network security relate to one another. Their focus is on long-run transaction fees, whereas we focus on endogenous reward rate and transaction dynamics. Empirically, a recent article by Augustin, Chen-Zhang, and Shin (2022) characterizes the risk and return trade-offs of yield farming using data from PancakeSwap. We offer likely the first theoretical framework to think about returns to DeFi staking, UIP violations, and crypto carry, with empirical corroborating evidence.

Finally, studies in international finance examine uncovered interest rate parity (e.g., Fama, 1984; Lustig, Stathopoulos, and Verdelhan, 2019). Carry and its predictability have been analyzed not only for currencies but also for other assets such as equities (e.g., Fama and French, 1998; Griffin, Ji, and Martin, 2003; Hou, Karolyi, and Kho, 2011), bonds (e.g., Ilmanen, 1995; Barr and Priestley, 2004), and commodities (e.g., Bailey and Chan, 1993; Casassus and Collin-Dufresne, 2005; Tang and Xiong, 2012). Koijen et al. (2018) apply a general concept of carry and find that carry predicts returns in both the cross-section and time series. We add by documenting UIP violations and carry premia among cryptocurrencies (and with fiat currencies). Recent empirical studies corroborate our findings by documenting deviations from covered interest parity (Franz and Valentin, 2020) and various forms of carry trades involving crypto derivatives (Christin et al., 2023; Schmeling, Schrimpf, and Todorov, 2023), and cryptocurrency with loanable programs (Fan et al., 2024). We do not rely on interest rates indirectly inferred from derivative markets or from a particular exchange with crypto lending programs. More importantly, we provide a tokenomics theory rationalizing the observations and significant crypto carry profits.

The remainder of this paper is structured as follows. Section 2 sets up a dynamic model of staking and token pricing. Section 3 characterizes the equilibrium to illustrate key mechanisms and convey economic intuition. Section 4 discusses how transaction fees, emission policies, and user heterogeneity affect the baseline economy. Section 5 introduces the data and describes stylized facts. Section 6 presents empirical findings that corroborate our theory. Section 7 concludes.

2 A Model of Tokenized Economy with Staking

2.1 Model Setup

In a continuous-time economy with infinite horizon, a continuum of agents optimally allocate individual wealth in a general digital marketplace (e.g., a tokenized blockchain platform, henceforth referred to as "the platform") where they can conduct peer-to-peer transactions using the platform native token, or participating in staking programs by temporarily locking up some tokens for network services and contribution (e.g., consensus recordkeeping, liquidity provision, or improving system security in DeFi protocols).

Platform productivity and token price. As in Cong, Li, and Wang (2021b,a), productivity A_t captures the general usefulness and functionality of the platform, i.e., the convenience users obtain by transacting on the platform using its tokens. We assume that A_t evolves endogenously:

$$dA_t = \mu^A(\Theta_t)A_t dt + \sigma^A A_t dZ_t^A, \tag{1}$$

where Θ_t is the endogenous staking ratio, i.e., the ratio of the aggregate number of staked tokens to the total number of tokens. It constitutes a potential state variable that influences token prices and agent decisions. In base layers (pan-PoS consensus protocols) and/or higher layers (DeFi applications and Layer 2 projects), staked tokens contribute to the development of the platform by maintaining node operations, facilitating the achievement of consensus, and increasing the security level of the network, respectively. Therefore, a higher staking ratio typically improves platform productivity, i.e., the drift of A_t is weakly increasing in Θ_t.[5]

Without loss of generality, we denote the token price (in units of the numéraire) as P_t, which is endogenously determined by A_t, the token issuance (total supply) Q_t, and external demand shocks (e.g., regulatory changes, market sentiment swings, and noise trading that are independent of (A_t, Q_t)) captured in a Markov stochastic process S_t satisfying $dS_t/S_t = \mu^S dt + \sigma^S dZ_t^S$ with one source of Brownian innovations $\left\{Z_t^S, t \geq 0\right\}$, which is independent of the productivity

[5]Staking could hurt platform productivity if the staker competition is so fierce that fewer stakers participate. Instead of allowing μ^A to potentially decrease in Θ_t, we capture this by explicitly modeling the staking competition. Also, we work under the risk-neutral measure with an exogenous stochastic discount factor $r^f > 0$, therefore μ_t^A already accounts for the price of risk for systematic shock that correlates to the platform productivity shock Z_t^A. As in Cong, Li, and Wang (2021b), we can derive a productivity dynamic in physical measure via a change of measure.

shock Z_t^A. The token price, $P_t = P(A_t, Q_t, S_t)$, should then follow a general diffusion process with endogenous and potentially time-varying μ_t, σ_t and η_t, which we shall solve for:

$$dP_t = P_t\mu_t dt + P_t\sigma_t dZ_t^A + P_t\eta_t dZ_t^S. \tag{2}$$

Agents, adoption, and transaction convenience. A platform agent is someone who uses tokens either for staking or transactions. We normalize the continuum of agents to be one unit measure. Agents gain convenience from holding tokens and conducting economic activities on the platform.[6] Similar as in Cong, Li, and Wang (2021b,a), for an agent holding x_t (in numéraire, positive) worth of tokens on the platform, the transaction convenience yields a utility flow of:

$$dv_t = x_t^{1-\alpha}(N_t A_t)^\alpha dt - x_t r^f dt. \tag{3}$$

With $\alpha \in (0,1)$, the marginal transaction convenience $\frac{\partial v}{\partial x} > 0$ and decreases with x. N_t represents the active network scale, measured as the share of circulating tokens. A larger N_t implies it is easier to find a transaction counterparty on the platform. In an extreme case, when all the tokens are staked (locked), holding a tradable token obtains no transaction convenience, as there is no counterparty. The transaction convenience increases in N_t as well as the productivity A_t. Holding tokens on the platform for transactions or staking means that the agent also loses the risk-free interests r^f on their value.[7]

Staking, staking rewards and convenience loss. Agents can stake part of their token holdings, $\theta_t x_t$ ($\theta_t \in [0,1]$), for staking rewards but suffer a convenience loss from locked value. In the baseline, we assume homogeneous agents to illustrate the economic mechanisms and implications. We later consider agents with heterogeneous staking preferences in Section 4.4.

Staking rewards incentivize agents to stake their tokens to either generate consensus records in a base layer or participate in some DeFi program, such as a liquidity pool or insurance pool. In practice, staking rewards come from fees others pay and additional token issuance (emission). To model staking rewards from newly issued blocks, we assume that the total amount of tokens at time t, Q_t, follows a general dynamic process: $dQ_t = E_t Q_t dt$, where E_t is the "emission rate"

[6]In an earlier draft, we model risk-averse agents who also consume offline. All main results remain, but the more complicated setup offers no additional insights.

[7]Even though we focus on token convenience as a medium of exchange, the reduced-form convenience could also include other utility flows such as governance and voting rights.

policy and is public information at the time of staking.[8] Any emission will increase token supply and thus generate an "inflation" expectation.

We denote the rewards from the transaction fees (e.g., ETH gas) as $F(A_t)Q_t$. $F'(A_t) \leq 0$, as one of the critical signs of a productive platform is lower transaction costs.[9] Transaction fees can be understood as continuing capital gains received by stakers.[10] The total amount of tokens distributed as rewards R_t then becomes:

$$R_t = R(A_t, Q_t) = [E_t + F(A_t)]\, Q_t. \tag{4}$$

All staked tokens are fungible and consequently all stakers face an instantaneous reward rate akin to interest rates on bank deposits:[11]

$$r_t \equiv \frac{R_t}{L_t}, \tag{5}$$

where L_t is the total amount of staked tokens. Largely aligned with practice, R_t here depends on exogenous emission and fee policies, and is treated as given in agents' decision-making.[12]

Agent with $\theta_t x_t$ worth (in numéraire) of staked tokens incur additional cost flows of (i), risk of slashing $c_t \theta_t x_t \mathrm{d}t$ proportional to their staking amount for simplicity, $c_t < r_t$, and (ii), numéraire

[8]The emission schedule is typically public information at the time of staking (or at least estimated based on real-time blockchain data, see Online Appendix OA1). As token supply could be well controlled by the ecosystem designer (Jermann, 2023), we consider a deterministic Q_t for simplicity; E can still vary over time. We discuss in Section 4 how a platform designer may want to endogenize fee designs as well as the emission policy.

[9]Lowering transaction costs is one of the key developing directions of these digital platforms, e.g. moving to PoS from PoW, and layer-2 innovations. The ETH gas fee of a transaction in practice entails a burned base fee and a priority fee paid to the validator as a tip. Online Appendix OA1 contains more details.

[10]Homogeneous agents' transaction convenience can be viewed as net of fees paid. Then their capital gains from transaction fees are essentially from external demands.

[11]For simplicity, we do not model the term structure of staking rewards—the focus of John, Rivera, and Saleh (2022). In our continuous-time setting, we only need staked tokens to be locked for dt. In our empirical tests, we only require agents to know the next period's reward emission.

[12]R_t may be also affected by total stakes L_t. Here we only require that the policies guarantee that r_t weakly decreases in L_t, as is observed in practice. Many programs fix the total amount of rewards. Broadly, L_t may decrease F by generating competition on validating transactions, which depreciates the priority fees (see the definition and operation on the official website of Ethereum and blocknative). As for emissions E, L_t may weakly decrease E, e.g., the reward rate of Ethereum's Gasper takes the form of $k/\sqrt{L}$. Otherwise, staking would be more like cooperation and generate quite low liquidity to the ecosystem. Jermann (2023) offers an in-depth analysis on optimal policies across a generalized form of $kL^{-1/s}$.

convenience loss from locked value, in light of Bansal and Coleman (1996); Valchev (2020),

$$\mathrm{d}\Psi_t \equiv (\theta_t x_t)^{\beta}(x_t N_t u)^{1-\beta}\mathrm{d}t, \tag{6}$$

where $\beta > 1$, so that $\frac{\partial \Psi}{\partial \theta_t} > 0$ captures the increasing marginal cost of locked values, which is also an alternative expression of the decreasing marginal convenience of holding numéraire.[13] Greater onchain wealth x_t and staking preference u decrease the convenience loss. Agents may hold different staking preference u_i. We omit the subscript i in the following when not adding confusion. In addition, a greater fraction of circulating tokens N_t also decreases the convenience loss, since a greater active network scale indicates that the tokens, once unlocked, are more liquid in exchange for numéraire offline. We have defined two convenience terms because we have three "assets": staked tokens, tradable tokens, and offline numéraire.[14]

2.2 Agents' Stochastic Control Problem

Taking as given the staking reward rate r_t, each agent decides at time t a portfolio consisting of $\theta_t x_t$ numéraire-equivalent amount of staked tokens and $(1-\theta_t)x_t$ numéraire-equivalent amount of tradable tokens, and maximizes the expected life-time payoff under the risk-neutral measure,

$$\mathbb{E}\left[\int_0^\infty e^{-r^f t}\mathrm{d}y_t\right], \tag{7}$$

where the utility flow $\mathrm{d}y_t$ depends on not only transaction convenience and staking rewards, but also an investment payoff from endogenous token price change:

$$\begin{aligned}
\mathrm{d}y_t &= \max_{\{x_t \geq 0, \theta_t \in [0,1]\}} \left\{0,\ \mathrm{d}v_t + (r_t - c_t)\theta_t x_t \mathrm{d}t - \mathrm{d}\Psi_t + x_t \frac{\mathbb{E}[\mathrm{d}P_t]}{P_t}\right\} \\
&= \max_{\{x_t \geq 0, \theta_t \in [0,1]\}} \left\{\begin{array}{l} 0,\ x_t^{1-\alpha}(N_t A_t)^{\alpha} + (r_t - c_t)\theta_t x_t \\ \qquad\qquad - (\theta_t x_t)^{\beta}(x_t N_t u)^{1-\beta} + x_t(\mu_t - r^f) \end{array}\right\}\mathrm{d}t.
\end{aligned} \tag{8}$$

[13] Imagine that one has a total wealth constraint, then less staked means more liquid holdings (offline numéraire and tradable tokens), which generates lower marginal numéraire convenience.

[14] Alternatively, one can separately define convenience terms of tradable and staked tokens each relative to the numéraire: transaction convenience is only obtained by tradable tokens, $[(1-\theta_t)x_t]^{1-\alpha}(N_t A_t)^{\alpha}$, and the convenience loss only accounts for locked values, $\mathrm{d}\Psi_t = (\theta_t x_t)^{\beta}[(1-\theta_t)x_t N_t u]^{1-\beta}\mathrm{d}t$. All implications go through except that the optimal θ_t lacks an analytical solution. That $\mathrm{d}\Psi_t$ is linear in x_t reflects a fixed unit cost for on/offline exchanges.

Note that if we allow $\theta_t x_t$ to generate less convenience loss, our framework can be used to study the recent popular "liquid staking" that surpassed decentralized lending in TVL, where stakers can get staking rewards without being restricted by the lock-up.[15]

2.3 Endogenous Staking Ratio and Market Clearing

Staking ratio. The overall staking ratio, Θ_t, the ratio of the aggregate number of staked tokens L_t to the total number of tokens Q_t, is a resulting control under system states, r_t, A_t, and the aggregation of agents' states,

$$\Theta_t \equiv \frac{L_t}{Q_t} = \frac{L_t P_t}{Q_t P_t} = \frac{\int_{i\in[0,1]} \theta_{i,t} x_{i,t} \mathrm{d}i}{\int_{i\in[0,1]} x_{i,t} \mathrm{d}i}. \tag{9}$$

Θ_t can be viewed as a continuous function of r_t. Staking ratio is important because it links individual choices with global states.

Equilibrium reward. According to (5), r_t is influenced by the aggregate stake, L_t, and thus by the aggregation of agents' controls, Θ_t. Then the equilibrium staking reward rate r_t^* solves:

$$r_t^* = r(\Theta^*(r_t^*)). \tag{10}$$

Note that the reward rate decreases in Θ_t. We later show that all the agents' staking amount increases with r_t, which guarantees (10) to be a fixed-point problem with a unique solution r_t^*.

Denote ρ_t as the staking reward ratio: $\rho_t \equiv \frac{R_t}{Q_t} = E_t + F(A_t)$, and $r_t = \frac{\rho_t}{\Theta_t}$. Since ρ_t has a one-to-one correspondence with the equilibrium r_t^*, the equilibrium staking ratio can either be represented as $\Theta(\rho_t, A_t)$ or $\Theta^*(r_t^*, A_t)$. In our subsequent analysis, we use these two notations, while retaining the notation $\Theta(r_t)$ to emphasize the agents' response to the given reward rate.[16]

[15] See https://www.coindesk.com/markets/2023/02/27/liquid-staking-replaces-defi-lending-as-second-largest-crypto-sector/. This is achieved through wrapped tokens that allow unsupported assets to be traded, lent, and borrowed on DeFi platforms. Our example of Solana in Online Appendix is supported by liquid staking platforms such as Lido, as of 2022.

[16] In practice, ρ_t and r_t are both important characteristics in the staking economy. In most staking economies, especially most PoS chains, the aggregate reward ratio is commonly known or at least can be estimated, while the staking reward rate features the actual return that agents will earn like deposit rate.

Market clearing. The market clears at price P_t such that the total quantity of tokens Q_t equals the sum of token holdings accounting for the external demand shock S_t:

$$Q_t = S_t \int_{i\in[0,1]} \frac{x_{i,t}}{P_t} \mathrm{d}i, \tag{11}$$

which implies a Markov equilibrium with A_t, Q_t and S_t. Note from (9) and (11) that the token price simultaneously clears both the staking and non-staking markets to rule out arbitrage.

3 Model Solution and Implications

For each agent i, she optimally decides her allocation taking the aggregate staking levels and reward rate as given. Conditional on participating the platform ($x_{i,t} > 0$), the agents choose $(x_{i,t}, \theta_{i,t})$ to optimize $\mathrm{d}y_{i,t}$. The optimal $\theta_{i,t}$ solves

$$\theta^*_{i,t} = \min\left\{1, \left(\frac{r_t - c_t}{\beta}\right)^{\frac{1}{\beta-1}} N_t u\right\}. \tag{12}$$

$\theta^*_{i,t}$ is independent of $x_{i,t}$, implying the agent effectively decides the stake fraction and total on-chain wealth separately. In the homogeneous baseline, $\Theta_t = \theta^*_{i,t}$. Substituting (12) into (8) and denote $\Gamma_t = \min\left\{r_t - c_t - (N_t u)^{1-\beta}, (\beta-1)\left(\frac{r_t-c_t}{\beta}\right)^{\frac{\beta}{\beta-1}} N_t u\right\}$, the optimal $x_{i,t}$ solves

$$x^*_{i,t} = \left(\frac{1-\alpha}{r^f - \mu_t - \Gamma_t}\right)^{\frac{1}{\alpha}} N_t A_t. \tag{13}$$

Note that N_t is the share of circulating tokens, $N_t = 1 - \Theta_t$. Combining with the market clearing condition (11), the price P_t satisfies

$$P_t = \frac{(1-\Theta_t)S_t A_t}{Q_t} \left(\frac{1-\alpha}{r^f - \mu_t - \Gamma_t}\right)^{\frac{1}{\alpha}}. \tag{14}$$

Proposition 1. ***Equilibrium.*** *With states of the productivity A_t, total token supply Q_t and external shock S_t, the Markov equilibrium solves a unique pair of equilibrium staking ratio and reward rate*

(Θ_t^*, r_t^*) *from* (10) *and*

$$\Theta_t^* = \frac{\left(\frac{r_t^* - c_t}{\beta}\right)^{\frac{1}{\beta-1}} u}{1 + \left(\frac{r_t^* - c_t}{\beta}\right)^{\frac{1}{\beta-1}} u}, \tag{15}$$

which ensures (10) *to be a fixed-point problem,* $\Theta_t^* = \Theta^*(A_t) < 1$. (14) *uniquely solves* μ_t^* *as a function of* (P_t, A_t, Q_t, S_t).

Proposition 1 ensures that the economy has a Markov equilibrium with (A_t, Q_t, S_t) as states. Whereas Q_t is certain given the emission policies, S_t reflects outside uncertainty, and A_t represents the lifecycle of the platform development.

3.1 Rewards and Staking Activities

As mentioned in Section 2.3, the equilibrium staking status (Θ_t^*, r_t^*) is determined by the staking reward ratio ρ_t, which is to some extent under the platform's control. By solving (10) and (15), it is straightforward to see that a higher ρ_t incentivizes staking, as formulated by Proposition 2.

Proposition 2. ***Staking.*** *The staking reward ratio* ρ_t *and equilibrium staking ratio* Θ_t^* *satisfy*

$$\rho_t = \Theta_t^* \left[\beta \left(\frac{\Theta_t^*}{(1-\Theta_t^*)u}\right)^{\beta-1} + c_t\right]. \tag{16}$$

In particular, a greater staking reward ratio leads to both greater Θ^* *and* r^**, i.e.* $\forall \rho' > \rho > 0$,

$$\Theta^*(\rho') > \Theta^*(\rho), \quad r^*(\rho') > r^*(\rho), \tag{17}$$

therefore a greater equilibrium staking ratio is associated with a greater equilibrium reward rate.

Proposition 2 gives a general characterization of how aggregate staking reward affects staking ratio in equilibrium. Recall that there are two sources of staking rewards for incentivizing staking activities. First, the platform can adopt a higher emission rate. This effect can be interpreted as an inflation tax charging on the non-staked parts: emission causes a depreciation expectation of the token price. The tradable tokens earn agents transaction convenience but suffer the depreciation, while the staked tokens are compensated by the emission reward. If we allow agents to be heterogeneous in staking levels, as discussed later in Section 4.4, the emission will cause a wealth redistribution from transaction-focused agents (typically retail users) to investment-focused agents (typically node operators, big whales). This shares a similar spirit of John, Rivera, and Saleh (2022) who show staking redistributes wealth from short-term users to long-term users.

Second, a greater transaction fee paid as rewards can incentivize staking. The fee policy naturally relates to platform development, as developed platforms are likely to be able to process numerous transactions without congestion, thus charge a low fee. On the other hand, startup platforms with relatively low productivity provide low transaction convenience, forcing agents to move to stake pools. Therefore, the staking ratio decreases in the lifecycle of platform development. Section 4 provides more discussions on issues concerning platform lifecycle.

Proposition 2 also implies that a higher equilibrium staking ratio Θ is associated with a greater equilibrium reward rate r, as they jointly represent a greater ρ. This relationship also applies to cross-sectional comparisons between tokens. In addition, in practice, it takes time to achieve an equilibrium. The fixed-point problem indicates that a higher r (relative to the equilibrium) leads to an increase in the staking ratio, while the higher staking ratio then decreases r in the short run, and ultimately reaches a new equilibrium. Regarding these implications, we formalize the following testable hypotheses:

Hypothesis 1. ***Determinants of the staking ratio.***

H1a*: a higher staking reward ratio ρ is associated with a higher staking ratio Θ;*

H1b*: a higher share of wealthy investors is associated with a higher staking ratio Θ;*

H1c*: a higher reward rate r predicts an increase in staking ratio Θ in the short term.*

3.2 Staking Ratio & Price Dynamics

Consider the impact of staking activities on the price given by (14). First, staking ratio directly enters the productivity drift μ_t^A, so it could endogenously determine μ_t. Second, P_t is affected by the scale of active network N_t, which is endogenized by the staking ratio.

We formally derive the pricing formula with endogenous staking ratio. By Proposition 1, μ_t

is a function of (P_t, A_t, Q_t, S_t). Applying Itô's Lemma to $P_t = P(A_t, Q_t, S_t)$, we have

$$\begin{aligned} \mathrm{d}P_t = &\left[\frac{\partial P_t}{\partial A_t} A_t \mu_t^A + \frac{\partial P_t}{\partial Q_t} Q_t E_t + \frac{\partial P_t}{\partial S_t} S_t \mu^S + \frac{1}{2}\frac{\partial^2 P_t}{\partial A_t^2}(A_t \sigma_t^A)^2 + \frac{1}{2}\frac{\partial^2 P_t}{\partial S_t^2}(S_t \sigma^S)^2\right]\mathrm{d}t \\ &+ \frac{\partial P_t}{\partial A_t} A_t \sigma^A \mathrm{d}Z_t^A + \frac{\partial P_t}{\partial S_t} S_t \sigma^S \mathrm{d}Z_t^S. \end{aligned} \tag{18}$$

Substituting into (2), we obtain

$$\mu_t = \frac{1}{P_t}\left[\frac{\partial P_t}{\partial A_t} A_t \mu_t^A + \frac{\partial P_t}{\partial Q_t} Q_t E_t + \frac{\partial P_t}{\partial S_t} S_t \mu^S + \frac{1}{2}\frac{\partial^2 P_t}{\partial A_t^2}(A_t \sigma_t^A)^2 + \frac{1}{2}\frac{\partial^2 P_t}{\partial S_t^2}(S_t \sigma^S)^2\right]. \tag{19}$$

Combined with the market clearing condition (14), a simple manipulation yields a partial differential equation (PDE) of $P_t = P(A_t, Q_t, S_t)$,

$$\begin{aligned} 0 = &\frac{\partial P_t}{\partial A_t} A_t \mu^A(\Theta(A_t)) + \frac{\partial P_t}{\partial Q_t} Q_t E_t + \frac{\partial P_t}{\partial S_t} S_t \mu^S + \frac{1}{2}\frac{\partial^2 P_t}{\partial A_t^2}(A_t \sigma_t^A)^2 + \frac{1}{2}\frac{\partial^2 P_t}{\partial S_t^2}(S_t \sigma^S)^2 \\ &+ \left[\Gamma(A_t) + (1-\alpha)\left(\frac{(1-\Theta(A_t))S_t A_t}{P(A_t, Q_t, S_t)Q_t}\right)^\alpha - r^f\right] P(A_t, Q_t, S_t). \end{aligned} \tag{20}$$

The pricing formula (20) differs from a Black-Scholes-type PDE. First, the "theta" term in Black-Scholes (BS) equation, which reflects the variation of the derivative value over time, is absent, as there is no maturity. Instead, $\frac{\partial P_t}{\partial Q_t} Q_t E_t$ captures the impact of expected inflation from token issuance. Second, since the platform productivity A_t is not a tradable underlying asset, the coefficient of $\frac{\partial P_t}{\partial A_t}$ is $A\mu^A$ instead of the stochastic discount factor Ar^f, and similarly for $\frac{\partial P_t}{\partial S_t}$. Finally, there is a "flow" term, $\left[\Gamma(A_t) + (1-\alpha)\left(\frac{(1-\Theta(A_t))S_t A_t}{P(A_t, Q_t, S_t)Q_t}\right)^\alpha - r^f\right] P(A_t, Q_t, S_t)$, that reflects the excess gain from staking rewards and transaction convenience offsetting the staking cost and loss of numéraire convenience.

(20) is also comparable to the token pricing formula in Cong, Li, and Wang (2021b) (CLW) with the following distinctions related to staking. First, staking reshapes the flow term: staking rewards yield an additional flow, Γ_t, and staking ratio affects the flow from transaction convenience, $(1-\alpha)\left(\frac{(1-\Theta_t)S_t A_t}{P_t Q_t}\right)^\alpha$. Given that the flow term is a unique feature of token pricing in CLW, reflecting how platform adoption is priced, staking activities fundamentally drive token's valuation by affecting adoption incentives. Second, staking also directly contributes to platform development, represented by the endogenized $\mu^A(A_t)$. In addition, there are two differences aris-

ing from model settings. (i) Staking rewards partially come from token issuance. This motivates us to consider a dynamic token supply $\mathrm{d}Q_t$, which is kept constant in CLW; (ii) Whereas CLW focuses on the network effect, represented as an endogenous adoption scale in the transaction convenience, here S_t can account for an adoption scale exogenously affected by demand shocks.[17]

The PDE in (20) captures the token price trajectory, while it still needs additional restrictions based on economic intuition to obtain a unique price dynamic from the solution manifold. Consider the impact of token supply. The drift of Q_t affects the total onchain wealth, as it induces inflation. However, as agents decide onchain allocations according to the worth in numéraire (e.g., treat one \$2 token as equal to two \$1 tokens), their onchain wealth should be independent of the Markovian state Q_t, the number of tokens. Similarly, note that the Markovian state S_t enters the agent's optimized utility solely as a linear multiplier of transaction benefits: the greater the aggregate external demand shock is realized, the more wealth is allocated onchain accordingly. Then the onchain worth scaled by S_t should be independent of S_t.[18] Denote $W_t = \frac{P_t Q_t}{S_t}$, then the above two observations indicate $\frac{\partial W_t}{\partial Q_t} = \frac{\partial W_t}{\partial S_t} = 0$.

Consider the boundary conditions. A useless platform ($A_t \to 0$) attracts no adopters, and the token should have no value. Therefore,

$$\lim_{A_t \to 0} P(A_t, Q_t, S_t) = 0, \quad \forall Q_t > 0, S_t > 0. \tag{21}$$

When the platform productivity A_t is sufficiently large, the token price follows the Gordon Growth Formula with a constant price drift $\lim_{A_t \to \infty} \mu_t = \tilde{\mu}_t$. Since $\rho'(A_t) < 0$ and $\rho > 0$, $\Theta(A_t)$ converges to a certain $\tilde{\Theta}_t \in (0, 1)$. Then $\Gamma_t = \tilde{\Gamma}_t$ is also constant. Therefore, we have an asymptotic boundary condition as $A_t \to \infty$,

$$\lim_{A_t \to \infty} \left[P(A_t, Q_t, S_t) - \frac{(1 - \tilde{\Theta}_t) S_t A_t}{Q_t} \left(\frac{1 - \alpha}{r^f - \tilde{\Gamma}_t - \tilde{\mu}_t} \right)^{\frac{1}{\alpha}} \right] = 0, \quad \forall Q_t > 0, S_t > 0. \tag{22}$$

Proposition 3. ***Token pricing formula.*** *The token price is uniquely solved by $P_t = W_t S_t / Q_t$ with boundary conditions (21) and (22), $\forall A_t, Q_t, S_t > 0$, where $W_t = W(A_t)$ satisfies the following*

[17] For example, sentiments. If we allow S_t to be a function of A_t, we can endogenize sentiments somewhat, though it is not our focus.

[18] Technically, these two intuitions add a Markov property that the equilibrium token price is Markovian in A_t, Q_t and S_t separately. In Appendix A, we provide further discussion of this property.

ordinary differential equation (ODE):

$$
\begin{aligned}
0 = {} & W'(A_t)A_t\mu^A(A_t) + \frac{1}{2}W''(A_t)(A_t\sigma^A)^2 \\
& + \left[\Gamma(A_t) + (1-\alpha)\left(\frac{A_t(1-\Theta(A_t))}{W(A_t)}\right)^{\alpha} - E_t + \mu^S - r^f\right] W(A_t).
\end{aligned} \tag{23}
$$

The economic implications of (23) are similar to the discussion of (20). In particular, the agents' response to the expected inflation, E_t, is reflected as a negative flow term of the onchain wealth, whereas the expected external demand drift μ^S generates a positive flow. Proposition 3 also indicates the uniqueness of the whole system, which allows for further numerical exploration. We plot the joint dynamics of the equilibrium staking ratio Θ_t and expected price appreciation μ_t with A_t as the state variable in Figure 1, which shows Θ_t and μ_t are positively related. Since the staking ratio can be computed from onchain information, it helps predict price changes.

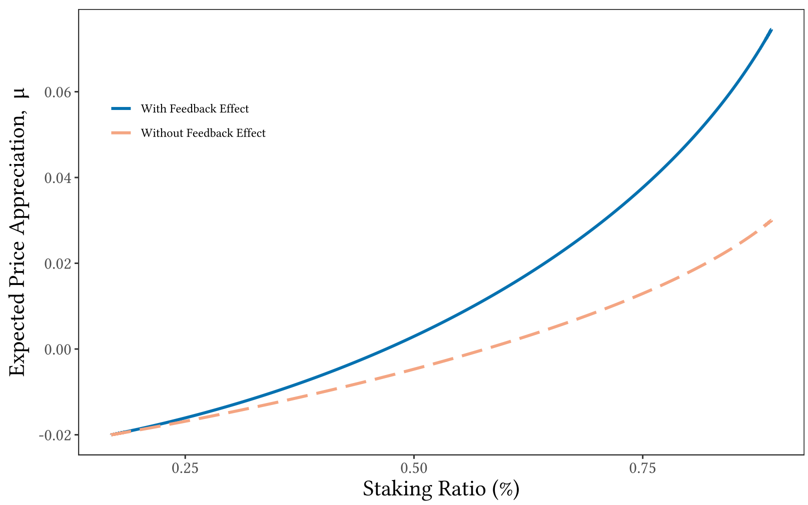

Figure 1: Staking ratio and price dynamics.
This graph shows the joint relationship between the system staking ratio Θ_t and the price drift μ_t. The blue curve is the case where the staking ratio feeds back the platform productivity A_t process (the main model), while the orange curve shows the case for comparison where the feedback effect does not exist.

The positive relationship between Θ_t and μ_t is driven by two economic forces. First, there is an *adoption effect* directly from the productivity A_t. On the one hand, μ_t decreases in A_t. As A_t grows, agents allocate more wealth on the platform, thus the potential future inflow is reduced, and so does the lower expected price appreciation. Mathematically, this effect is represented as the greater "flow" term in the ODE (23) lowering the derivatives that make up μ_t. On the other hand, Θ_t also declines in A_t in equilibrium, because higher A_t results in greater transaction convenience compared to staking rewards. Therefore, the joint dynamics of μ_t and Θ_t exhibit a positive relationship. Such force does not rely on the feedback mechanism but in general a phenomenon from market participation, so we can see from Figure 1 that even without the feedback effect (the orange curve), μ and Θ are positively related. In addition, staking reduces the active network scale (or the onchain liquidity) N_t, therefore a higher staking ratio slightly reduces the aggregate onchain wealth allocation, amplifying the above joint relationship. This channel generates the similar user-base stabilizing effect of tokens as discussed in Cong, Li, and Wang (2021b).

The second is the *feedback effect* of staking on the A_t process. As (1) shows, a high staking ratio increases the productivity drift μ_t^A, and then leads to a large price drift μ_t. This force accounts for the role that staking plays in platform growth. In PoS, the system state with a relatively high staking ratio implies a strong network of highly engaged validators, so that the consensus and confirmation are efficiently reached. As for high-layer staking economy such as DeFi applications, with a certain capital value, a high staking ratio relates to a high TVL (total value locked), which is recognized as improving the security level of the platform. For both layers of the staking economy, the staking ratio positively impacts the growth of platform productivity A_t through the above-mentioned paths respectively, therefore resulting in a greater drift. As a reflection of the value of the platform, the price drift increases according to Itô's Lemma (19).

In practice, the way that staking contributes to the platform varies across blockchains and platforms, and may lack transparency and stability. However, with the combination of both the adoption and feedback mechanisms, we conclude the following general predictions.

Hypothesis 2. ***The predictability of the staking ratio on price appreciation.***

H2a: *the staking ratio Θ positively predicts token returns.*

H2b: *a long-short token portfolio sorted by staking ratios is profitable.*

Furthermore, external shock S_t, which captures risk factors and behavioral patterns in practice, influences price as a sentiment shifter rather than as a direct component of the ODE (23). This helps explain why sother risk cannot fully account for the predictability of staking ratio.

3.3 UIP Violation and Crypto Carry

From Sections 3.1 and 3.2, we note that the staking ratio connects the staking reward rate and price appreciation. While staking reward rates function similarly to deposit interest rates, token price changes resemble exchange rate fluctuations against the numéraire. This analogy allows us to draw insights from research on the foreign exchange market to better understand the implications of staking dynamics.

Denote the financial excess return of unit staked token over the numéraire by λ_t,

$$\mathrm{E}_t[\lambda_t] \equiv \mathrm{E}_t\left[\mathrm{d}P_t + P_t(r^{\text{staked token}} - r^f)\right]/P_t = \mu_t + r_t - c_t - r^f. \tag{24}$$

If UIP holds in the crypto market — meaning that the expected returns on default-free deposits across currencies are equalized — then $\mathrm{E}_t[\lambda_t]$ should be zero. In other words, $\mathrm{E}_t[\lambda_t]$ should not be predictable by observable variables. However, consider an agent who stakes tokens to maximize financial excess returns. She faces a trade-off: while staking provides financial returns, it also comes at the cost of losing the convenience of holding the numéraire or liquid tradable tokens. Then the staking reward should not only offset the price changes, but also cover the convenience loss. This implies that $\mathrm{E}_t[\lambda_t]$ is positive, reflecting the convenience wedge between holding tokens versus the numéraire, which violates the UIP, a phenomenon in conventional assets (e.g., Krishnamurthy and Vissing-Jorgensen, 2012; Valchev, 2020; Jiang, Krishnamurthy, and Lustig, 2021).

Here the fiat numéraire (e.g., US dollar) is the local currency and the platform token is the foreign currency. By adopting any other cryptocurrency as the numéraire, we can verify that the UIP violation is not restricted to fiat-crypto relationships but also exist across digital assets.

What makes the UIP violation of stakable tokens special compared to that in other markets? The convenience wedge here is *endogenously* affected by the staking ratio and therefore predictable. Recall Proposition 2, a higher equilibrium staking ratio corresponds to a greater reward rate r_t. Meanwhile, Section 3.2 shows that a higher staking ratio predicts higher price appreciation μ_t. As a result,

$$\mathrm{E}_t\left[\lambda_t|\Theta_t'\right] > \mathrm{E}_t\left[\lambda_t|\Theta_t\right], \quad \text{provided} \quad \Theta_t' > \Theta_t, \tag{25}$$

which is a stronger version of the UIP violation. In particular, staked tokens differ fundamentally from fixed deposits in several key ways. First, the reward rate is automatically and continuously adjusted based on aggregate staking activity; Second, the bank does not prioritize pricing the fiat money, while the platform actively prices the tokens. Importantly, since staking participation is endogenously influenced by token emission and fee policies, the platform is somewhat able to manipulate the convenience wedge. This makes the staking mechanism extremely critical in a tokenized economy.

The violated UIP leads to a direct corollary of profitable carry trades.[19] Following Koijen et al. (2018), the crypto carry is similarly defined as the currency carry:

$$\text{carry}_t \equiv \frac{r_t - c_t - r^f}{1 + r^f}. \tag{26}$$

In summary, the predictability of staking ratios on excess returns implies:

Hypothesis 3. ***UIP violation and crypto carry premium.***

H3a: *the uncovered interest rate parity (UIP) is violated among stakable tokens.*

H3b: *crypto carry trade strategies are profitable.*

H3c: *carry predicts excess return in tokens.*

4 Platform Lifecycle: Fees, Emission, and Heterogeneity

We next examine how transaction fees, emission policies, and user heterogeneity affect the staking economy and the platform lifecycle.

4.1 Platform Lifecycle and the Convenience Wedge

Staking reward rates and token price changes are jointly influenced by the platform productivity, and are interconnected through endogenous staking participation. Staking in turn feeds back to the productivity drift. This suggests that the platform has the ability to shape its development lifecycle by adjusting staking incentives.

When platform productivity is low, staking requires significant financial compensation due to the convenience loss relative to the numéraire. To provide sufficient incentives, the platform may increase token issuance, which inevitably devalues the token price. As token holders shift their allocations from transactions to staking, the future reward rate declines, while the convenience wedge increases. For staking to remain viable, price appreciation from staking participation must

[19] In the exchange market, a carry trade goes long in baskets of currencies with high interest rates and short in low ones. In general, the concept of carry applies to a host of asset classes, e.g., equities, bonds, commodities, treasuries, credits, and options (Koijen et al., 2018). Its predictability of excess returns and investment performance are widely documented and studied (e.g., Lustig, Roussanov, and Verdelhan, 2014; Bakshi and Panayotov, 2013; Burnside et al., 2011; Menkhoff et al., 2012; Koijen et al., 2018; Daniel, Hodrick, and Lu, 2017).

offset the convenience loss. As discussed in Section 3.2, this mechanism relies on two driving forces: the adoption effect and the feedback effect, without which the staking economy is unsustainable. In other words, a staking project is likely a scam if it lacks both a network-effect-driven business model and a mechanism through which staking directly contributes to platform growth.

When platform productivity is high, the convenience wedge is minimal, and transaction usage dominates onchain allocations. At different stages, the platform may adjust staking incentives over time to manage different phases of its lifecycle. Due to the endogenous contribution of staking, such adjustments also influence the pace of the platform's development and its long-term sustainability.

4.2 Transaction Fees

Transaction fees can be treated as a direct cash flow from platform users to stakers (validators or operators). Productive (well-developed) platforms typically feature lower transaction fees, while the platform retains some discretion in setting its fee policy.[20]

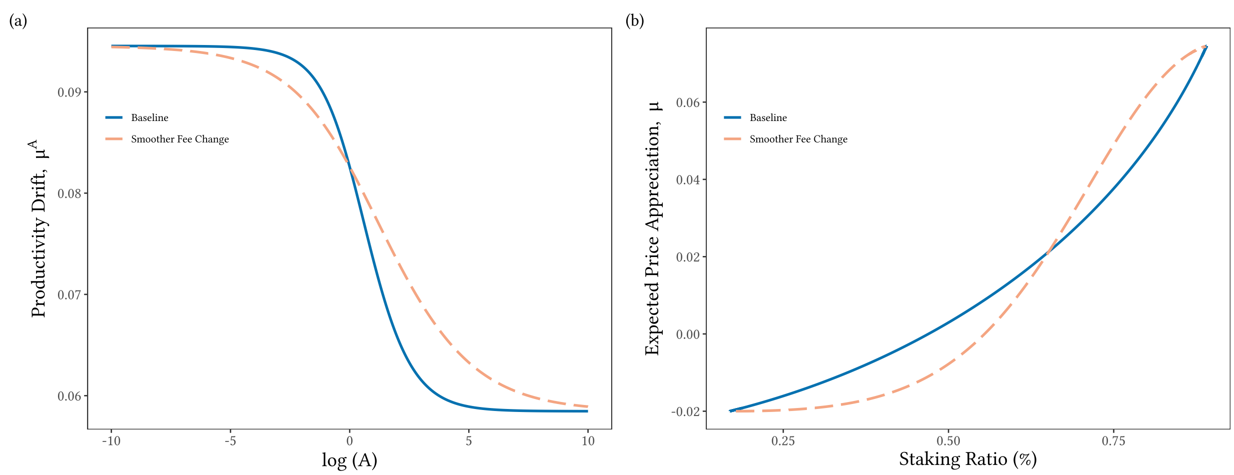

Figure 2: Platform lifecycles under different transaction fee policies.
Panel (a) shows the relationship between log productivity $\log(A)$ and productivity drift μ^A; Panel (b) shows the relationship between staking ratio Θ (%) and expected price appreciation μ. The blue curves represent the baseline (the same case as the blue curve in Figure 1), while the orange curves correspond to the case where the transaction fee $F(A)$ changes (decreases) more smoothly with A, i.e., the fee starts to decrease earlier but at a lower speed as the platform grows.

[20]For example, Layer-2 scaling is considered a critical improvement that significantly reduces transaction costs and alleviates network congestion.

Figure 2 considers an alternative fee specification from the baseline. To focus on fee changes within the platform cycle, we set the maximum (minimum) fee when the platform productivity is extremely low (high) as constant and independent of the platform's decision. A smoother fee change (shown in orange curves) refers to that as the platform grows, the fee starts to decrease earlier but at a lower speed. Panel (a) shows a more gradual platform development lifecycle under a smoother fee adjustment. This is because the staking ratio becomes less sensitive to productivity fluctuations, which also implies a more stable active network scale. As Panel (b) shows, changes in fee policies can alter both the quantitative relationship and convexity between the staking ratio and price appreciation. For instance, when the equilibrium staking ratio declines to 75% as the platform evolves, a platform with smoother fee adjustments experiences slower growth and, consequently, lower productivity. However, due to the adoption effect, the platform still generates greater expected price appreciation compared to a platform with a more abrupt fee reduction. In this sense, the choice of fee policies reflects the platform's strategic priorities during its lifecycle, particularly in the early stages. A platform may prioritize either a large and relatively stable active user base or rapid productivity growth, depending on how it structures its fee adjustments.

4.3 Token Issuance

Staking rewards also come from newly issued tokens (emission). In addition to the similar mechanism as in fee changes, token issuance has a direct impact on the price by generating expected inflation. That is, token issuance represents an inflation tax paid by users to stakers.

Figure 3 shows the platform lifecycles under different token issuance designs. As Panel (a) shows, compared to the benchmark blue curve, a higher emission rate (shown by the orange curve) always leads to a higher productivity drift, as it provides stronger incentives for staking. In particular, token issuance provides a stronger toolkit than fee policies when the platform productivity is large enough, at which stage fee changes have a diminished impact because fees are generally too low to make a significant difference. As Panel (b) shows, the higher emission rate always leads to lower price appreciation, as it generates greater inflation. Meanwhile, the equilibrium staking ratio increases, as agents stake more in response to the higher inflation tax relative to that in the benchmark.

In addition, the platform can design a more complex issuance policy, probably dynamic over the lifecycle, e.g., decreasing with the platform productivity, as shown by the red curves. Higher

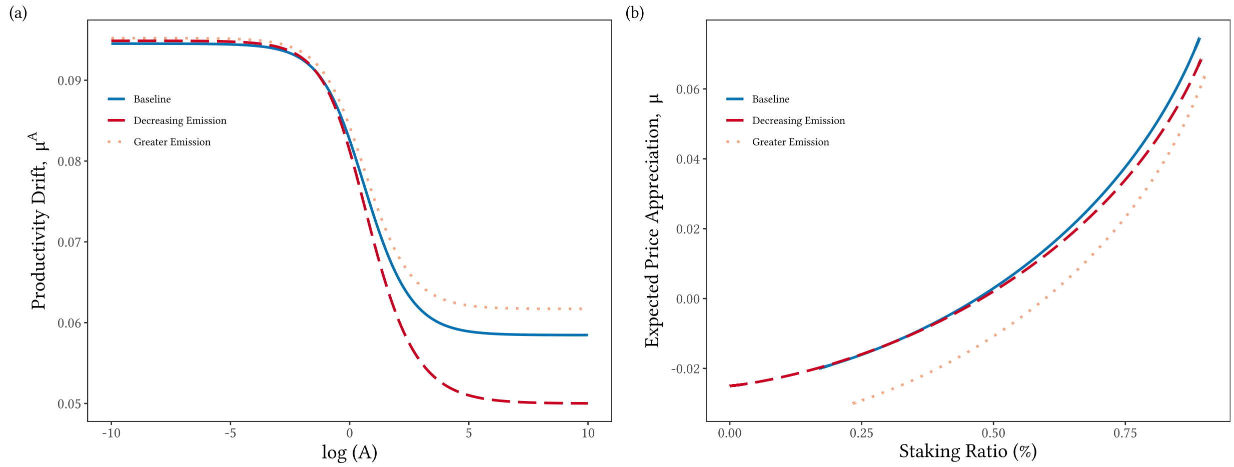

Figure 3: Platform lifecycles under different token issuance designs.
Panel (a) shows the relationship between log productivity $\log(A)$ and productivity drift μ^A; Panel (b) shows the relationship between staking ratio Θ (%) and expected price appreciation μ. The blue curves represent the baseline constant emission rate (the same case as the blue curve in Figure 1). The orange curves show the case with a greater emission rate. The red curves show an issuance design where the emission rate mechanically decreases in platform productivity.

emission in the initial stage accelerates user adoption, while decreasing emission as the platform grows mitigates the impact of inflation.[21]

4.4 Staking Preference and User Heterogeneity

The agents' staking preference u affects their trade-off between participating in onchain activities and staking. A greater u reflects a higher tendency to stake or, equivalently, a lower preference for onchain transaction needs. As Figure 4 (a) shows, given any fixed productivity, platform with a lower staking tendency obtains lower expected price appreciation μ. Recall the adoption effect and feedback effect, a lower staking tendency leads to a smaller staking fraction and a larger active user base, therefore reduces the platform's contribution and lowers expected future adoption. From another perspective, the lower price appreciation can also be interpreted as the result of a lower staking level (locked share) reducing the liquidity premium under the same transaction demand. As Panel (b) shows, a lower staking tendency results in an overall lower

[21]Here we do not discuss the optimal distribution strategy for the platform, especially over the full lifecycle, as platforms may have various objectives. Jermann (2024) solves the optimal issuance for PoS tokens where the objective is defined as the lifetime welfare produced by the platform.

staking level that fluctuates within a narrower range, making price appreciation more sensitive to changes in staking ratios.

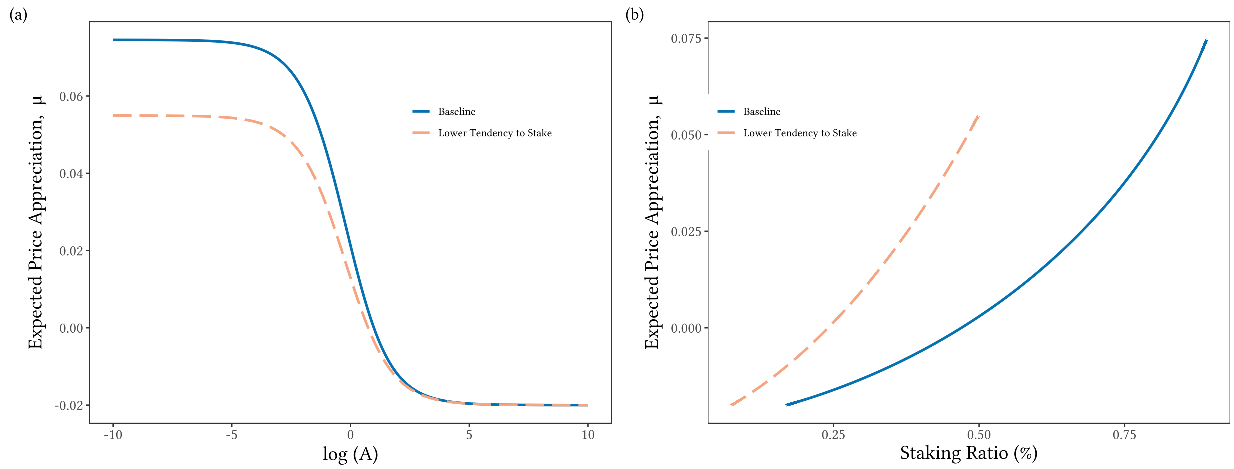

Figure 4: Platform parameters under different aggregate user staking tendencies. Panel (a) ((b)) shows the relationship between log productivity $\log(A)$ (staking ratio Θ) and expected price appreciation μ. The blue curves represent the baseline (the same case as the blue curve in Figure 1). The orange curves show the case with a lower aggregate staking tendency u.

Furthermore, agents may have heterogeneous staking preference $u_i \geq 0$. For example, people have a decreasing marginal consumption needs as their wealth increase. Then wealthier agents are expected to have a higher staking preference. The heterogeneous optimal staking is:

$$\theta^*_{i,t} = \min\left\{1, \left(\frac{r_t - c_t}{\beta}\right)^{\frac{1}{\beta-1}} N_t u_i\right\}. \tag{27}$$

When u_i is sufficiently high, an agent chooses to specialize in staking without participating in onchain transactions. Then the active network share N_t is reduced relative to the homogeneous-agent benchmark. This in turn incentivizes agents with low u_i to reduce their staking levels. As a result, this helps to rationalize why in practice, especially when platforms become large, a division of labor emerges where large asset owners and exchanges dominate PoS validation and earn staking revenues, while retail agents primarily function as pure platform users.

The above discussion uncovers interesting potential mechanisms related to wealth heterogeneity. Denote the cumulative distribution function of the staking preference u over the agents as $G(u)$. Since agents with equal u_i are the same in every respect, an agent with greater initial wealth can be treated as a group of investors with the same u_i. Therefore, the shape of G in a way captures wealth and other related user heterogeneity. The derivation and general implications of the Markov equilibrium in Section 3 still apply when considering $G(u)$ as an additional state.[22]

5 Data and Stylized Facts

5.1 Data on Stakable Tokens

To empirically examine Hypothesis 1, 2 and 3, we collect our main data from *Stakingrewards.com*, arguably the largest collector of information related to staking covering historical and real-time data on most stakable assets. To ensure the representativeness of the sample and to accommodate potential survivorship bias, we identify the major stakable tokens at two distinct time points in 2020 and 2021, respectively, and track their data from July 2018 to November 2022. The resulting dataset covers daily observations of 66 tokens including Ethereum 2.0, represents the majority of the staking economy's market cap, and contains early projects that have failed as of 2022. Specifically, our sample set makes up 37.78% of the total cryptocurrency market capitalization by the end of 2021 (64.34% when excluding Bitcoin), and respectively consists 80.35% of the PoS market and 97.88% of the DeFi market.[23] The sample period covers the initial birth and rapid growth of "staking," as well as the bear market during 2022. Additional information about staking is typically aggregated from the official websites of each token, including details of staking participation methods (see Online Appendix OA1), reward sharing rules, real-time staking amount (staking ratio), etc.

Table 1 displays the summary statistics. In most analyses, we also aggregate the daily observations into weekly and monthly data. Panel B shows the large dispersion among tokens in reward rate, staking participation, and price returns: the mean staking reward rate ranges from 0.02% to 75.39%, while the mean staking ratio ranges from 2.78% to 97.77%.

[22] A more general way to characterize wealth heterogeneity is to introduce the wealth distribution of the population. One can imagine that people present different wealth dynamics since they make heterogeneous staking choices. We examine this complex system in a separate study, where the evolution of the wealth distribution and agents' dynamic staking decisions constitute a mean-field game.

[23] According to *CoinMarketCap* and *StakingRewards*. The sample set includes 48 base-layer pan-PoS protocols and 29 high-layer DeFi platform tokens. The two are not mutually exclusive as mentioned.

Table 1: Summary statistics.
Panel A summarizes the main raw variables. Their token-grouped means and standard deviations of the raw daily observations are calculated and summarized in Panel B.

Panel A: Raw variables.

	Daily			7-Day			30-Day		
	N	Mean	Std.Dev	N	Mean	Std.Dev	N	Mean	Std.Dev
Reward Rate, r (%, Annual)	41,003	13.42	17.78	5,867	13.28	16.05	1387	13.16	15.69
Reward Ratio, ρ (%)	39,546	6.31	8.86	5,660	6.26	8.58	1339	6.20	8.47
Staking Ratio, Θ (%)	41,706	46.37	23.06	5,964	46.39	23.09	1415	46.36	23.13
Price Appreciation, r_{price} (%)	43,114	-0.04	7.25	6,091	-0.34	22.93	1391	-2.13	54.42
Δr	40,788	-0.03	7.86	5745	-0.13	4.68	1,301	-0.51	8.76
$\Delta\Theta$	41,505	0.00	1.33	5851	0.03	3.37	1,333	0.03	6.25

Panel B: Group-summarized values.

	N	Mean	Std.Dev	Min	25%	Median	75%	Max
$mean(r), (\%)$	66	14.86	15.44	0.02	6.33	9.84	15.77	75.39
$sd(r), (\%)$	66	7.21	10.39	0.01	1.43	2.47	9.60	43.69
$mean(\Theta), (\%)$	65	44.05	22.22	2.78	27.26	44.22	59.61	97.77
$sd(\Theta), (\%)$	65	8.16	5.98	0.27	3.50	6.81	11.69	25.48
$mean(r_{price}), (\%)$	66	-0.01	0.50	-1.17	-0.23	0.04	0.15	2.72
$sd(r_{price}), (\%)$	66	6.76	3.05	3.89	5.53	6.25	6.80	23.88

5.2 Stylized Facts about Staking and Token Pricing

Aggregate trends. The shift of focus away from PoW and onto the PoS consensus algorithms have been evident and timely.[24] The PoS share has increased substantially over time from 5% in Oct. 2019 to over 20% in Oct. 2021. As of Oct. 2021, the PoS market cap reached $326.775 Billion with annual growth rate 1,550%, while the overall crypto market cap is up by 673%. The entire staking economy has grown to over 4 million total users by the end of 2021. During our sample period (2018-2022), the staking economy is known to have gone through a full bull/bear cycle along with the cryptocurrency market.

Staking rewards and token price returns. The study of stakable tokens is related to international finance. Token price and staking reward rate can be compared to exchange rates and interest rates. Figure 5 illustrates the excess return in the next week against the interest rate spread calculated as the "foreign interest rate" minus the "local interest rate." Each grey dot represents a weekly data point for a particular token and the blue line shows a linear fit. The upward

[24] According to 2021 Staking Ecosystem Report by *StakingRewards*.

slope indicates that an increase in the foreign interest rate (relative to the local one) is associated with an increase in the excess return on the token over the local currency, i.e., the crypto version of the "UIP puzzle," which is formally tested and discussed in Section 6.3.

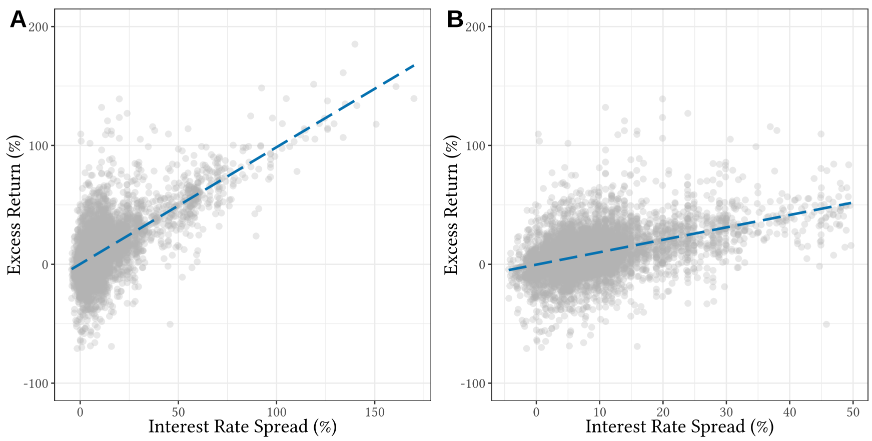

Figure 5: Reward rate spread and token exchange rate.
This figure shows the relationship between the reward (interest) rate spread and the token excess return (exchange rate and interest spread). We treat US dollar as local currency and the 1Y treasury interest (obtained from Fed) rate as the local interest rate. Each dot in the a weekly data point for a particular token. The staking reward rate (annualized) is treated as the foreign interest rate, and the x-axis, the interest rate spread, is calculated as the foreign interest rate minus the local interest rate. The y-axis is the excess return in the next week, i.e., interest rate spread plus the price appreciation. Panel A shows the whole sample set, whereas Panel B limits the interest rate spread to a relatively common range ($< 50\%$). The blue line shows linear fitting of the scatter points in each panel.

6 Empirical Findings

6.1 Linking Reward Rate and Wealth Concentration to Staking

To test **(H1a)**, we first calculate the daily average of aggregate staking reward ratio $\bar{\rho}$ and staking ratio $\bar{\Theta}$ for each token over its entire sample period. Figure 6 plots their pooling relationship, in which each token generates one dot. The positive-sloped linear fit indicates that the reward is positively related to the staking ratio. This pattern implicitly illustrates that averaging over the time series roughly conforms to the equilibrium. The positive correlation still holds even with a larger slope after removing high-influential points with $\bar{\rho} > 15\%$. We also test the relationship under earlier data coverage (up to Oct. 2020) in Panel B. Although there are fewer stakable tokens, the significant positive correlation still exists, suggesting the relationship is robust against sample periods.

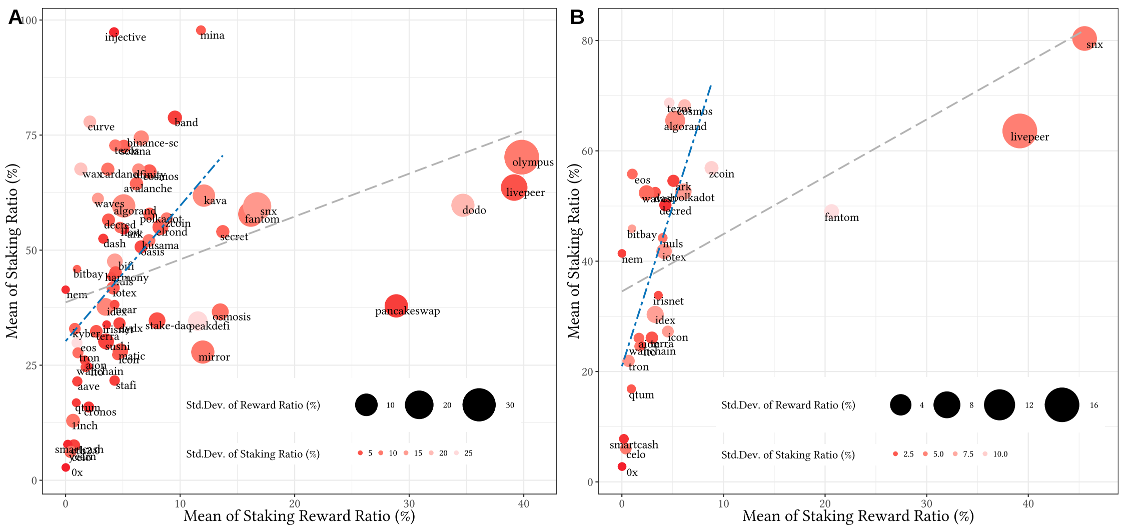

Figure 6: Staking reward versus staking ratio.
This figure corresponds to **(H1a)**, the relationship between staking reward ratio ρ and staking ratio Θ. In Panel A, each token generates one point by calculating its mean Θ and ρ over the sample period. The size and color of the points indicate the standard deviations of ρ and Θ respectively. The gray dashed line is the linear fit. The blue line is the fit after removing the influential points with $\bar{\rho}$ larger than 15%. Panel B plots the same patterns under earlier data coverage (up to Oct. 2020).

We further test **(H1a)** in panel regressions (Table 2). We use the staking ratio of token i at time t, $\Theta_{i,t}$, as the dependent variable, and the staking reward ratio, $\rho_{i,t}$, as the main independent. As Column (1) shows, the estimated coefficient implies a 10-percentage-points higher aggregate reward ratio is associated with a 7.79-percentage-points ($se = 1.90$) higher staking ratio. After inducing time-varying platform controls and investment-related controls, the corresponding estimates decrease to about 3.7 points yet still significant. Monthly sample period and two-way fixed effects are considered. As suggested by Petersen (2008); Abadie et al. (2017), we cluster standard errors on both token and time dimensions together with the fixed effects, which addresses potential heterogeneity in the treatment effects. The positive correlation remains robust. Recall that staking essentially acts as an inflation tax, i.e., facilitates redistribution from more usage-focused adopters to richer or investment-focused adopters. A larger staking reward ratio corresponds to a heavier tax and, forces lower usage preference.

The time-varying token-specific controls bring alternative intuitions in line with our model: (i) the equilibrium staking ratio negatively relates to the platform productivity, captured by the proxy variable $a_{i,t}$, since it increases transaction convenience with certain staking rewards;[25] (ii) the share of large-asset users (big whales), $whale_{i,t}$, positively relates to staking ratio. This links to heterogeneity and **(H1b)**, and will be discussed specifically later. In addition, token age is a concern as it usually relates to reward designs. Incipient platforms may have not distributed tokens to many agents, thus should be associated with lower staking. We capture age effects by two dummies, $NotLaunched_{i,t}$ and $Y^0_{i,t}$, which equal 1 when the token is in the stage before and within one year of launching on exchanges, respectively. Table 2 corroborates the common hypothesis relating to token age.

(H1a) focuses on contemporaneous correlations in equilibrium. As mentioned, it takes time to achieve equilibrium in practice, then **(H1c)** expects the reward rate r should predict future staking ratio Θ in short terms (transition process). Also, when agents face multiple tokens, the predictability could appear in the cross-section. Table 3 reports the tests for **(H1c)**. We use the change in staking ratio, $\Delta\Theta_{i,t} = \Theta_{i,t} - \Theta_{i,t-1}$, as the dependent variable, and the previous reward rate, $r_{i,t-1}$, as the main independent. The estimated coefficients are all positive, implying that a larger reward rate predicts a positive change in staking ratio, e.g., column (6) shows that if the annual reward rate increases by one percentage point, the staking ratio will increase by 0.026 ($se = 0.015$) percentage points in the following week. This can be a large effect considering the magnitude of the changes in the rewards rate in the staking economy. Previous staking ratio $\Theta_{i,t-1}$ is controlled to capture the potential diminishing marginal effects. Time-varying platform controls are also considered, which do not exhibit significant influences. This is reasonable since the platform characteristics enter the equilibrium, but their impact on the transition process could be complex. In addition, the statistical predictive power decreases as the time window expands. This is partly due to the accumulation of noise over a longer time period. More importantly, the longer period makes the predicted impact already reflected in the formation of new equilibrium.

Wealth concentration and aggregate staking. Agents may be heterogeneous in staking preference. In particular, large-asset agents (whales) tend to stake more, implying that when the tokens are more concentrated in whales, the equilibrium staking ratio would be higher. We test this hypothesis **(H1b)** in columns (5) and (9) of Table 2, where the coefficients of $whale_{i,t}$ are significantly positive. That is, concentration implies additional general tendencies to staking.

[25]The proxy variable of platform productivity $a_{i,t}$ is measured as the average onchain transaction processing per second. Appendix B discusses the choice of this proxy.

Table 2: Staking ratio with respect to the staking reward ratio.

This table tests **(H1a)**, i.e., a higher aggregate staking reward ratio $\rho_{i,t}$ is associated with a higher staking ratio $\Theta_{i,t}$, as proved by the positive coefficients of $\rho_{i,t}$. Controls include token age, captured by two dummies, $NotLaunched_{i,t}$ and $Y^0_{i,t}$, which equal 1 when the token is before, and within one year of launching on mainstream exchanges, respectively; the proxy of platform productivity, $a_{i,t}$; the value share of tokens held by big-asset accounts, $Whale_{i,t}$, the token market cap, and price volatility. The positive estimated coefficients of $Whale_{i,t}$ additionally proves **(H1b)**, i.e., a higher share of large investors is associated with a higher staking ratio $\Theta_{i,t}$. Token and time effects are fixed. Sample sets with different horizons (weekly and monthly) are tested. Standard errors clustered in both token and time dimensions in parentheses. ***,**,* indicate statistical significance at the 1%, 5% and 10% respectively.

Dependent:	$StakingRatio_{i,t}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	7-Day					30-Day			
$\rho_{i,t}$	0.779***	0.428**	0.429**	0.360**	0.374**	0.794***	0.439***	0.413**	0.431**
	(0.190)	(0.162)	(0.161)	(0.170)	(0.173)	(0.188)	(0.155)	(0.155)	(0.173)
$NotLaunched_{i,t}$			-0.076	-0.162**	-0.183**			-0.113**	-0.130**
			(0.064)	(0.063)	(0.064)			(0.053)	(0.051)
$Y^0_{i,t}$			0.004	-0.059	-0.073			-0.028	-0.042
			(0.030)	(0.047)	(0.045)			(0.038)	(0.037)
$a_{i,t}$				-0.747***	-0.417**			-0.623***	-0.415***
				(0.158)	(0.159)			(0.143)	(0.098)
$\frac{1}{100}\log(Cap)_{i,t}$				1.686	1.991			1.124	1.582
				(1.756)	(1.719)			(1.843)	(1.809)
$\frac{1}{100}Volatility_{i,t}$				0.236	0.328			1.590	0.965
				(0.344)	(0.397)			(1.806)	(1.459)
$Whale_{i,t}$					0.217***				0.171**
					(0.071)				(0.075)
Token FE		Yes	Yes	Yes	Yes		Yes	Yes	Yes
Time FE		Yes	Yes	Yes	Yes		Yes	Yes	Yes
Observations	5,660	5,660	5,660	1,364	1,364	1,339	1,339	308	308
R^2	0.088	0.811	0.812	0.917	0.920	0.089	0.801	0.929	0.931

Importantly, if staking benefits the platform in a fundamental way (such as enhancing network security), wealth concentration may not be all bad — large stakeholders are more interested in becoming facilitators of the platform's services than pure users. Agents, on the other hand, may have incentives to pursue larger usage benefits at the cost of more concentration, as discussed in Section 4.4. In practice, staking/voting pools for prominent platforms are often backed by large exchanges and foundations, which is consistent with the findings here.

Table 3: Staking ratio with respect to the staking reward rate.

This table tests **(H1c)**, i.e., staking reward rate positively predicts staking ratio. The dependent is the change of staking ratio, $\Delta StakingRatio_{i,t}$, and the main independent is the reward rate in the previous period, $r_{i,t-1}$. Controls include token age, proxy of previous platform productivity, previous percentage of tokens held by big-asset accounts that are similar in previous tables, and previous staking ratio, $StakingRatio_{i,t-1}$ that capturing potential diminishing marginal effect. Token and time effects are fixed. Sample set with different horizons (weekly and monthly) are tested. Standard errors clustered in both token and time dimensions in parentheses. ***,**,* indicate statistical significance at the 1%, 5% and 10% respectively.

Dependent:	$\Delta StakingRatio_{i,t}$								
	Daily					7-Day		30-Day	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$r_{i,t-1}$	0.002***	0.003***	0.001**	0.001**	0.002*	0.026*	0.030	0.049**	0.006
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.015)	(0.024)	(0.020)	(0.019)
$StakingRatio_{i,t-1}$			-0.009***	-0.009***	-0.016***		-0.103***		-0.294***
			(0.002)	(0.002)	(0.004)		(0.028)		(0.057)
$NotLaunched_{i,t}$				-0.001	-0.002*		-0.009		-0.029
				(0.001)	(0.001)		(0.006)		(0.021)
$Y^0_{i,t}$				0.000	-0.001		-0.006		-0.012
				(0.000)	(0.001)		(0.005)		(0.016)
$a_{i,t-1}$					0.005		0.018		0.046
					(0.006)		(0.047)		(0.107)
$Whale_{i,t-1}$					0.003		0.019		-0.002
					(0.002)		(0.011)		(0.036)
Token FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39,359	39,359	39,359	39,359	10,636	5,559	1,511	1,266	344
R^2	0.0006	0.043	0.049	0.049	0.172	0.063	0.197	0.124	0.322

6.2 Staking Ratio and Token Price Dynamics

Table 4 reports the tests for **(H2a)**, i.e., staking ratio positively predicts token price changes. We calculate the log token price change, $r_{price_{i,t}} = \log(\frac{P_{i,t}}{P_{i,t-1}})$, and regress it on the previous staking ratio. We consider the cryptocurrency-market and token-size factors that have important impacts on price changes as discussed in Liu, Tsyvinski, and Wu (2019). The estimated coefficient of staking ratio is significantly positive, indicating that a higher staking ratio predicts larger token price appreciation, e.g., column (4) shows that if the staking ratio of a token increases by one percentage point, its price will appreciate by 6.6 basis points (0.06%, $se = 0.023\%$) in the next week. Recall the large variation in the staking ratio, this effect can have a large impact on price.

Table 4: Staking ratio and token price.

This table tests **(H2a)**, i.e. staking ratio predicts token price appreciation. The dependent $r_{price_{i,t}}$ is the log price change. The main independent is the staking ratio in the previous period, $StakingRatio_{i,t-1}$. Controls include the market return MKT_t, the log market cap $\log(Cap)_{i,t-1}$, the proxy of network adoption $\Delta Network_{i,t-1}$, the price return of the previous period $r_{price_{i,t-1}}$, and rolling CAPM beta, $\hat{\beta}_{i,t}$. Token characteristic controls include the token age, platform productivity, capital share held by big-asset accounts. We also do the test in different time spans and with token-specific and time fixed effects. Standard errors clustered in both token-specific and time dimensions in parentheses. ***,**,* indicate statistical significance at the 1%, 5% and 10% respectively.

Dependent:	$r_{price_{i,t}}$								
	Daily			7-Day			30-Day		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$StakingRatio_{i,t-1}$	0.009**	0.027***	0.022**	0.066***	0.172**	0.138*	0.208*	0.347*	0.372**
	(0.004)	(0.007)	(0.008)	(0.023)	(0.068)	(0.071)	(0.121)	(0.197)	(0.139)
MKT_t	0.968***	1.029***		0.844***	0.685*		2.445*	2.201	
	(0.031)	(0.043)		(0.264)	(0.352)		(1.435)	(1.496)	
$\hat{\beta}_{i,t}$			-0.002			-0.037			-0.132
			(0.002)			(0.031)			(0.104)
$\log(Cap)_{i,t-1}$	-0.002***	-0.002**	-0.005***	-0.027***	-0.031***	-0.038***	-0.120***	-0.121***	-0.113***
	(0.000)	(0.001)	(0.001)	(0.006)	(0.009)	(0.009)	(0.034)	(0.043)	(0.021)
$r_{price_{i,t-1}}$		0.021	0.035		0.008	-0.075*		0.127*	-0.076
		(0.050)	(0.060)		(0.040)	(0.042)		(0.062)	(0.074)
$\Delta Network_{i,t-1}$		0.167***	0.224***		0.195	0.366		0.992	0.996
		(0.058)	(0.068)		(0.207)	(0.259)		(1.393)	(1.216)
$a_{i,t-1}$		0.047	0.069		0.603**	0.306		1.007	0.614
		(0.030)	(0.041)		(0.258)	(0.235)		(0.825)	(0.946)
$Whale_{i,t-1}$		-0.010	-0.013		-0.006	-0.103		-0.179	-0.253
		(0.009)	(0.009)		(0.086)	(0.073)		(0.341)	(0.201)
$NotLaunched_{i,t}$		-0.003	0.011***		0.075***	0.108**		0.119	0.159
		(0.002)	(0.004)		(0.024)	(0.040)		(0.154)	(0.126)
$Y^0_{i,t}$		0.002	0.007**		0.021	0.056**		-0.073	0.114
		(0.002)	(0.003)		(0.021)	(0.020)		(0.084)	(0.107)
Token FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE			Yes			Yes			Yes
Observations	41,544	10,887	9,991	5,872	1,530	1,434	1,347	334	322
R^2	0.267	0.346	0.478	0.043	0.054	0.507	0.120	0.207	0.640

This effect is robust against different time windows. Staking ratio has incremental predictive power with more control variables that have been suggested to affect the token's pricing in recent studies, including platform controls (token age, productivity, and whale share) for possible predictable price appreciation from platform characteristics, the previous returns for the potential momentum, and onchain network effects, $\Delta Network_{i,t-1}$.[26] To further consider the time-series auto-correlation, we adopt two-way fixed effects regression in columns (3), (6), and (9), where the estimated rolling CAPM β captures the forces from market fluctuations. The estimated coefficients remain significant and positive with two-way clustered standard errors.

Further discussion may lie in the heterogeneous predictive power of staking ratio across tokens categories and market sentiment. We test the same specification on multiple sub-samples, including bull/bear sub-periods, pan-PoS/DeFi sub-samples in Appendix B. The estimated coefficients of $\Theta_{i,t-1}$ are all positive, among which only the bear-period exhibits lower statistical significance. This suggests the positive relationship between staking ratio and expected price appreciation to be a generally existing phenomenon in our sample.

Staking ratio and portfolio performance. As applications of such predictability, we also examine the performance of Θ-sorting portfolio to test **(H2b)**. The predictability of price appreciation suggests that high staking ratio tokens should bring excess returns over the low ones. We test it by creating a long-short strategy, that is, sort the tokens by their staking ratio by the end of previous period, equal-weighted long the top 50% and short the bottom. The allocation is adjusted every week. Figure 7 and Table 5 document that the portfolio provides relatively stable positive cumulative returns with a Sharpe ratio of 0.865. To show that this is not another manifestation of the size effect, we test the same sorted strategy within the large-cap and small-cap token groups, respectively. The implication remains qualitatively robust. Table 5 suggests that the large-cap group performs weaker. It is partly because the staking ratio of these tokens are relatively low in general, and thus with smaller differences among each other. Considering the limitations on shorting in practice, we also test the long-only strategies, i.e., borrow US dollars and equal-weighted long top (bottom) 50% tokens sorted by staking ratio. The top group outperforms the bottom group, and also the full-sample benchmark.[27]

[26] It is measured by the lagged log differences in the total amount of addresses with non-zero balance on the platform. As Cong et al. (2021a) discusses, cryptocurrency returns exhibit network adoption premia. The estimated coefficient of the network adoption term is positive and consistent with prior research.

[27] We repeat this test using bitcoin denomination to cancel out the crypto market trend, the main results remain.

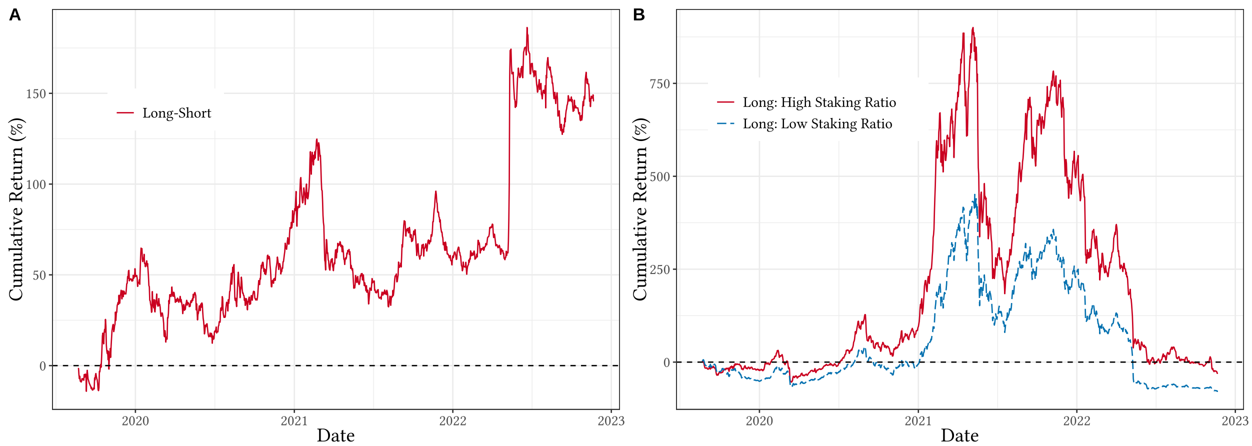

Figure 7: Cumulative returns of staking ratio sorted portfolios.
Panel A shows the cumulative return of the long-short portfolio sorted by staking ratios. Panel B shows the strategy that longs top 50% tokens with high staking ratios (in red solid line) and the bottom 50% tokens with low staking ratios (in blue solid line). The portfolio construction is detailed in Section 6.2.

Table 5: Statistics of staking ratio sorted strategies.
This table reports the statistics of portfolio performance. The upper panel reports the results of the long-short carry strategy, including long top 50% high staking ratio tokens and short bottom 50% across the full sample, i.e., corresponding to Figure 7 Panel A, and same strategies but within top 50% large-cap and small-cap groups, respectively. The lower panel reports equal-weighted long strategies, including the full-sample benchmark, long top 50% high staking ratio tokens, and long bottom 50%. The portfolios are rebalanced each week. For each strategy, the annualized mean, standard deviations, skewness, kurtosis, maximum drawdown (MDD) and Sharpe ratio are reported.

Strategy	Mean (Annual, %)	St.dev. (Annual, %)	Skewness	Kurtosis	MDD (%)	Sharpe Ratio (Annual)
Long-short Strategy:						
Full Sample	36.081	41.731	2.273	27.582	41.135	0.865
Within Large-Cap Group	18.575	56.857	5.881	104.942	70.057	0.327
Within Small-Cap Group	40.052	62.720	0.588	5.177	40.065	0.639
Long Strategy:						
EW All assets	15.577	78.244	−1.576	7.672	92.934	0.199
EW High-Staking Ratio	22.873	80.737	−1.161	5.042	93.013	0.283
EW Low-Staking Ratio	−13.207	79.823	−1.724	9.547	96.115	−0.165

6.3 UIP Violation and Crypto Carry

UIP violation. We test **(H3a)**, i.e., whether UIP is violated, using the specification in Fama (1984): define the excess return of token i at t as $\lambda_{i,t} = \log P_{i,t+1} - \log P_{i,t} + (r_{i,t} - c_i) - r_t^f$, and regress $\lambda_{i,t+1}$ on $r_t^f - r_{i,t} + c_i$ with coefficient B and token fixed effects,[28] where P_t is the price in local currency, r^f is the local interest. Under UIP, $B = 0$, i.e. the excess return is not forecastable by current interest rate differences. We examine different time horizons as Valchev (2020) does, and use different assets as local, including US dollar, Bitcoin, Ethereum and stakable ETH 2.0. Table 6 reports the findings. All results show significantly negative estimated B, implying that a high interest rate predicts a positive appreciation of the exchange rate, leading to arbitrage opportunities. We also use each single token as local currency, respectively. The regression results (reported in Appendix B) suggest the violation of UIP also exists within the crypto market.

Table 6: Test of UIP violation.

This table tests **(H3a)**, i.e., regressing excess returns on previous reward rate spread (with coefficient B) with token-specific effects. In each row, we use a different asset as local currency and report the estimated coefficients and standard errors (clustered by tokens) of B.

Local	7-day			30-day		
Currency	Coef., B	Std. Err.	R^2	Coef., B	Std. Err.	R^2
US Dollar	−1.02	(0.044)	0.33	−1.12	(0.176)	0.11
Bitcoin	−1.02	(0.034)	0.37	−1.08	(0.134)	0.11
Ethereum	−1.04	(0.033)	0.37	−1.09	(0.126)	0.12
Eth 2.0	−1.04	(0.014)	0.42	−1.25	(0.059)	0.17

Crypto carry trades. UIP violations naturally prompt us to examine the predictability of crypto carry to token excess return and the performance of the crypto carry trade portfolio **(H3b)**. Tokens in the asset pool are ordered by their carry in the previous period, and then divided into the top 50% and the bottom 50%. A carry trade portfolio is constructed by going long high-carry group with equal weight and going short low with equal weight at the end of each week. Long tokens are also staked to earn staking reward rates, while short tokens pays additional compensate for the staking reward rate. The portfolio is rebalanced every week.[29]

Figure 8 plots the cumulative returns. Table 7 reports the statistics of these strategies. The carry strategy has a significantly greater positive return and yields an annual Sharpe ratio of 1.60.

[28] While in practice, there are various ways to stake (e.g., delegating and running a node), which corresponds to different reward rates and costs, the staking programs mostly feature delegation/voting (that our data correspond to), which incurs negligible time-varying operational costs. We therefore assume $c_{\{i,t\}}$ for each token is constant (c_i) and eliminated by token-specific fixed effects.

[29] Most stakable tokens offer the flexibility of weekly staking or have derivatives that enable such an asset allocation. Considering the abnormal fluctuation when a staking project first launches, our weekly asset pool does not include new staking projects that appear within the past week.

Since we long high carry and short low carry, the portfolio carry is always positive. If the portfolio always achieves positive returns, it means that in the cross-section, assets with higher carry have greater aggregate returns. For higher moments, the strong positive skewness is associated with the currency carry trade shown by Brunnermeier, Nagel, and Pedersen (2008). Moreover, the carry strategy exhibits excess kurtosis, indicating fat-tailed positive and negative returns, which is consistent with Koijen et al. (2018)'s findings for currencies and commodities. The long-short carry trade strategy exhibits relatively stable returns, especially considering the high volatility of cryptocurrency markets and the bull/bear circle during 2020-2022.

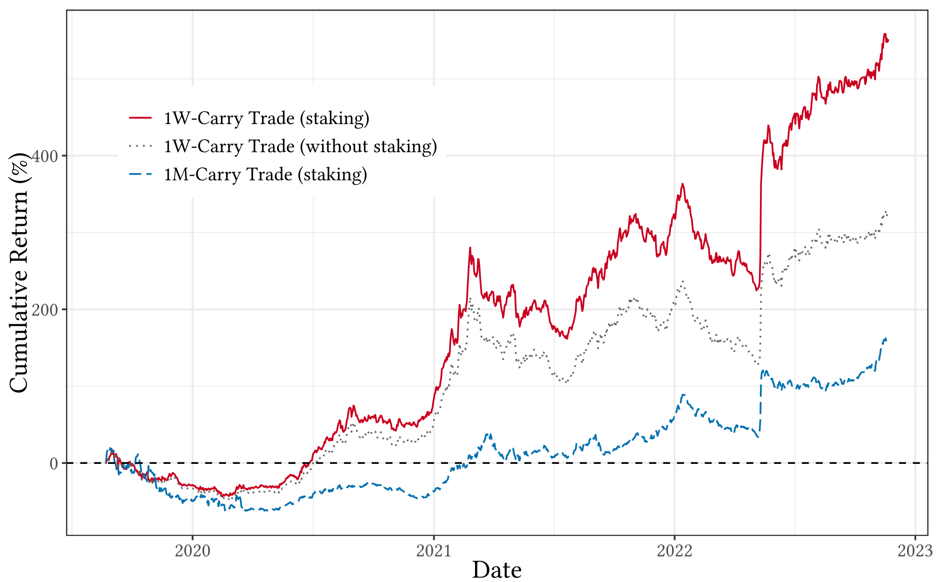

Figure 8: Cumulative returns of long-short carry trade strategies.
This figure examines **(H3b)**, i.e., crypto carry trade strategies are profitable. The red curve shows the cumulative return of the main long-short carry strategies, i.e., long top 50% high carry tokens and short the bottom 50%. The portfolio is rebalanced every week. The construction is detailed in Section 6.3. Compared to the red line, the gray curve plots the strategy without earning or compensating staking rewards, and the blue curve shows the strategy rebalanced every month.

We also report related strategies for comparison: (i) hold the same portfolio but without stake (and not compensate for staking); (ii) apply the same strategy but rebalance every month; (iii) considering the potential short-selling limits, examine the average return of equal-weighted full-sample / (top 50%) high-carry / low-carry tokens. The non-staking strategy also yields positive returns, implying that the excess returns are not only from carry (staking reward) also price appreciation. Moreover, the monthly-rebalanced strategy exhibits fewer returns. There are two explanations: (i) the reward rate decreases with contemporaneous staking ratio mechanically.

Table 7: Statistics of carry trade strategies.

This table corresponds to **(H3b)** and reports the statistics of carry trade strategies. The first three rows report the results of the long-short carry strategies as detailed in Section 6.3 and displayed in Figure 8. The rows below report long strategies. Annualized mean, standard deviations, skewness, kurtosis, maximum drawdown (MDD), and Sharpe ratio are reported.

Strategy	Mean (Annual, %)	St.dev. (Annual, %)	Skewness	Kurtosis	MDD (%)	Sharpe Ratio (Annual)
Long-short Strategy:						
1W-Carry Trade (Staking)	65.820	41.095	1.410	18.772	29.966	1.602
1W-Carry Trade (Non-staking)	52.497	41.104	1.404	18.719	35.920	1.277
1M-Carry Trade (Staking)	45.051	56.929	1.260	20.508	69.497	0.791
Long Strategy:						
EW All assets	15.577	78.244	−1.576	7.672	92.934	0.199
EW High Carry	49.416	81.309	−1.103	4.687	90.419	0.608
EW Low Carry	−16.404	80.444	−1.804	9.907	95.645	−0.204

Therefore, investors cannot consistently earn high carry over a long period without timely position adjustments; (ii) the reversal of reward rate further influences the staking ratio, which then weakens the effect on price appreciation. Finally, long-only strategies corroborate the carry premia: longing top 50% tokens with high carry outperforms the simple equal-weighted benchmark, while the bottom 50% performs the worst. Their cumulative returns plotted in Appendix B ensure the above observations.

Excess return predicted by carry. In **(H3c)**, the return predictability can come from both the crypto carry itself and any price appreciation that is related to or predicted by carry. We follow Koijen et al. (2018) to regress the overall excess return on the previous carry. Table 8 reports the estimations of the coefficient of carry, C. The results indicate that carry is a strong predictor of expected return. Without token-specific fixed effects, the estimated coefficient is approximately 1, indicating that tokens with high staking reward rates neither relatively depreciate nor appreciate on average. Hence, investors can earn the reward rate spread using carry trade. With token fixed effect, the estimated C become lower and even insignificant in monthly specifications.[30] This suggests time series carry predicts less expected return, which aligns with the staking mechanism

[30]Without token-specific and time-fixed effects, C represents the total predictability of returns from carry from both its passive and dynamic components. Token fixed effects will remove the predictable return component of carry that comes from passive exposure to tokens with different unconditional average returns.

in our model:[31] despite higher reward rates leading to higher staking ratios and price appreciations, there is a *downward adjustment effect* of the reward rate in the time series, where the reward rate is automatically adjusted to account for the increase in staking ratios. Then excess return is lowered by this adjustment. The downward adjustment becomes more pronounced as the time window expands, even allowing the economy to reach a new equilibrium staking level. Consequently, the estimated C in Columns (6) and (8) are smaller than (2) and (4), respectively. This reflects the consequence of the staking reward rate being determined by the competitive equilibrium characterized in our model.

Table 8: Carry and excess returns.

This table tests **(H3c)**. The dependent variable is the excess return, and the independent is the carry in the previous period. Standard errors clustered in both token-specific and time dimensions in parentheses. ***,**,* indicate statistical significance at the 1%, 5% and 10% respectively.

Dependent:	$\text{ExcessReturn}_{i,t}$							
	7-Day				30-Day			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Carry}_{i,t-1}$	0.956***	0.901***	0.968***	0.917***	0.968***	0.773	1.009***	0.846**
	(0.053)	(0.095)	(0.042)	(0.071)	(0.296)	(0.534)	(0.216)	(0.383)
Token FE		Yes		Yes		Yes		Yes
Time FE			Yes	Yes			Yes	Yes
Observations	5,745	5,745	5,745	5,745	1,301	1,301	1,301	1,301
R^2	0.230	0.239	0.441	0.447	0.038	0.094	0.333	0.374

7 Conclusion

Staking has become a hallmark feature in many distributed networks involving trillions of dollars. In addition to offering a convenience yield for transactions, blockchain-based tokens are frequently staked for base-layer consensus generation or for incentivizing economic activities in DeFi protocols and platform development, and consequently earn stakers rewards. We build a dynamic model of a token-based economy where agents endogenously allocate wealth on a

[31] This phenomenon is similarly found in commodities (Koijen et al., 2018) with a different mechanism: when a commodity has a high spot price relative to its futures price, implying a high carry, the spot price tends to depreciate on average, thus lowering the realized return on average below the carry.

digital platform and use tokens either to earn rewards or to transact. We solve for the equilibrium with stochastic controls and both supply (i.e., productivity) and demand (i.e., investor sentiment) shocks, and identify staking ratio as a fundamental variable linking staking to the endogenous reward rate and token price. Data on stakable tokens corroborate our model predictions. The staking ratio is proportional to the reward rates in the cross-section but negatively correlated to reward rates in the time series; it positively predicts cryptocurrency returns. Furthermore, the model rationalizes violations of the uncovered interest rate parity, and we document significant related profitable trading strategies and crypto carry premia.

The framework can be explored further for studying the utilities of platform tokens. For example, DeFi projects increasingly lock up both native and non-native tokens. Allowing multiple tokens to be used within a network may cause the payment utility of native tokens to decline. But stakable tokens entitle the holders to instead collect rewards (fees and subsidies), while providing functionalities such as security or liquidity for the networks. Given that many platforms use staking to foster adoption and demand, optimally designing the various utilities of tokens and understanding their implications on token prices constitute interesting future research. Similarly, despite our initial discussions on how fees and emissions affect platform lifecycle in the presence of staking and potential user heterogeneity, it remains an open and important question how to best design token supply policy, fee mechanisms, and staking protocols jointly.

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Appendix

A Proofs

Proof of Proposition 1. First, we prove that given μ_t and other state variables, (10) is a fixed-point problem. Start from (12). If in (12), $\left(\frac{r_t-c_t}{\beta}\right)^{\frac{1}{\beta-1}} N_t u \geq 1$ so that $\theta^*_{i,t} = 1$, then $\Theta_t = 1$, $r_t = \rho_t < \infty$ and $N_t = 0$, which generates a contradiction. Therefore,

$$\Theta_t = \left(\frac{r_t - c_t}{\beta}\right)^{\frac{1}{\beta-1}} N_t u \quad \Rightarrow \quad \Theta_t = \frac{\left(\frac{r_t-c_t}{\beta}\right)^{\frac{1}{\beta-1}} u}{1 + \left(\frac{r_t-c_t}{\beta}\right)^{\frac{1}{\beta-1}} u}. \tag{A.1}$$

Combining with (10), a simple manipulation yields

$$\rho_t = \Theta_t \left[\beta \left(\frac{\Theta_t}{(1-\Theta_t)u}\right)^{\beta-1} + c_t\right]. \tag{A.2}$$

The LHS is constant given A_t, while the RHS increases in Θ_t. When $\Theta_t \to 0^+$, the RHS converges to zero; when $\Theta_t \to 1$, the RHS tends to infinity. Therefore, for any given positive ρ_t, the above equation solves a unique $\Theta_t \in (0, 1)$. Equivalently, it indicates that (10) is a fixed-point problem. In equilibrium, Θ^*_t solves (A.2) and $r^*_t = \rho_t / \Theta^*_t$, which are both functions of A_t.

Then $\Gamma_t = (\beta - 1)\left(\frac{r^*_t - c_t}{\beta}\right)^{\frac{\beta}{\beta-1}} (1 - \Theta^*_t) u$ is also a function of A_t. Then in (14), the RHS is monotonically increasing with μ_t, which means that given (P_t, A_t, Q_t, S_t), (14) solves a unique μ_t.

Proof of Proposition 2. (16) is directly obtained from (A.2), where the RHS is increasing in Θ. Therefore, a greater ρ_t corresponds to a greater unique Θ that satisfies (A.2). Therefore, $\forall \rho' > \rho > 0$, $\Theta^*(\rho') > \Theta^*(\rho)$. Similarly,

$$\rho_t = r^*_t \frac{\left(\frac{r^*_t-c_t}{\beta}\right)^{\frac{1}{\beta-1}} u}{1 + \left(\frac{r^*_t-c_t}{\beta}\right)^{\frac{1}{\beta-1}} u}, \tag{A.3}$$

where the RHS is increasing in r^*_t, and tends to zero (infinity) as r^*_t tends to zero (infinity). Therefore, r^* is one-to-one solved by ρ, $r^*(\rho') > r^*(\rho)$. (Θ^*_t, r^*_t) are jointly determined by ρ_t, therefore, a greater Θ_t^* is associated with a greater r_t^*.

Proof of Proposition 3. First, since $W_t = P_t Q_t / S_t$,

$$\frac{\partial P_t}{\partial A_t} = \frac{S_t}{Q_t}\frac{\partial W_t}{\partial A_t}, \quad \frac{\partial^2 P_t}{\partial A_t^2} = \frac{S_t}{Q_t}\frac{\partial^2 W_t}{\partial A_t^2}, \quad \frac{\partial P_t}{\partial Q_t} = -\frac{W_t S_t}{Q_t^2}, \quad \frac{\partial P_t}{\partial S_t} = \frac{W_t}{Q_t}, \quad \frac{\partial^2 P_t}{\partial S_t^2} = 0. \tag{A.4}$$

Substituting into (19), we obtain

$$\mu_t = \frac{\partial W_t / \partial A_t}{W_t} A_t \mu_t^A - E_t + \mu^S + \frac{1}{2}\frac{\partial^2 W_t / \partial A_t^2}{W_t}\left(A_t \sigma^A\right)^2. \tag{A.5}$$

Note that $\partial W_t / \partial S_t = \partial W_t / \partial Q_t = 0$, then $\partial \mu_t / \partial S_t = \partial \mu_t / \partial Q_t = 0$, i.e., μ_t is a function of $(W_t, A_t, \partial W_t / \partial A_t, \partial^2 W_t / \partial A_t^2)$. On the other hand, combining the equilibrium price (14) with $W_t = P_t Q_t / S_t$, we have

$$W_t = (1 - \Theta(A_t)) A_t \left(\frac{1-\alpha}{r^f - \mu_t - \Gamma(A_t)}\right)^{\frac{1}{\alpha}}. \tag{A.6}$$

Therefore, the above equation is actually a second order ODE of $W_t = W(A_t)$. Substituting (A.5) into (A.6), we obtain the explicit expression of the ODE, i.e. (23),

$$\begin{aligned} 0 = \; & W'(A_t) A_t \mu^A(A_t) + \frac{1}{2} W''(A_t)(A_t \sigma^A)^2 \\ & + \left[\Gamma(A_t) + (1-\alpha)\left(\frac{A_t(1-\Theta(A_t))}{W(A_t)}\right)^{\alpha} - E_t + \mu^S - r^f\right] W(A_t). \end{aligned} \tag{A.7}$$

Consider the boundary conditions. (21) indicates that $\lim_{A \to 0} W(A_t) = 0$. (22) indicates that

$$\lim_{A_t \to \infty}\left[W(A_t) - (1 - \tilde{\Theta}_t) A_t \left(\frac{1-\alpha}{r^f - \tilde{\mu}_t - \tilde{\Gamma}_t}\right)^{\frac{1}{\alpha}}\right] = 0, \tag{A.8}$$

where $\tilde{\mu}_t$ is solved as follows. According to the Gordon Growth Formula, $\lim_{A_t \to \infty} P_t = \tilde{K}_t A_t S_t / Q_t$, where $\tilde{K}_t$ is a constant involving $(\tilde{\Theta}_t, \tilde{\Gamma}_t, \tilde{\mu}_t)$. Therefore,

$$\lim_{A_t \to \infty} \frac{W'(A_t) A_t}{W(A_t)} = 1, \quad \lim_{A_t \to \infty} \frac{W''(A_t)}{W(A_t)} = 0. \tag{A.9}$$

Substituting into (A.5), we obtain $\lim_{A_t \to \infty} \mu_t = \tilde{\mu}_t = \mu^A(\tilde{\Theta}_t) - E_t + \mu^S$, which completely solves the boundary condition. With the two boundary conditions, the second-order ODE has a unique solution. Then given any (A_t, Q_t, S_t), the Markov equilibrium price $P_t = W_t S_t / Q_t$ is unique.

Discussion on the Markov property. As mentioned in the main text, we notice a critical observation to find the valid solution from the solution manifold of the PDE (20). That is, W_t is independent of Q_t and S_t. The economic logic is intuitive, e.g., for Q_t, people always decide the onchain allocation according to the worth in numéraire, therefore the total number of tokens, as a Markov state, only affects the instantaneous unit conversions but not the total onchain wealth.

Here we discuss why this condition is also valid technically. Typically, we need boundary conditions to uniquely solve P from the PDE (20). However, to solve a second order PDE with three variables, the two natural boundary conditions, (21) and (22), are not enough. The additional condition here effectively solves the solution is a particular form: $P(A, Q, S) = P_1(A)P_2(Q)P_3(S)$, where $P_2(Q) = 1/Q$ and $P_3(S) = S$ are determined by the economic intuition, and then $P_1(A) = W(A)$ can be uniquely solved given the two boundary conditions.

B Additional Figures and Tables

Robustness in sub-samples: bulls and bears. A common concern related to pricing factors is the different predictability in bulls and bears. Fortunately, our data set includes a complete bull and bear market cycle. Overall speaking, the cryptocurrency market was roughly in a bull market in 2020 and 2021, and entered into a bear market in the end of 2021. A more precise and simple way to classify market bulls and bears refers to Lunde and Timmermann (2004) with the corresponding amplitude thresholds set to 35% (bulls) and 25% (bears). We use Bitcoin price as the indicator of the market, which is a common approach in practical investments. Also, as Ethereum is playing an increasingly important role, especially with its significant place in the staking economy, we alternatively use Ethereum price as the indicator for robustness. Figure B.1 visualizes the segmentation of bulls and bears during the whole in-sample periods. We then regress the main empirical specification in Table 4 on sub-samples of bulls and bears. Columns (1)-(8) of Table B.1 reports the regression results. In general, the estimated coefficients of $StakingRatio_{i,t-1}$ are all positive across bulls and bears that divided by different indicators, as well as different horizons (daily and weekly). This suggests that the implication that staking ratio positively predicts price appreciation generally holds in bulls and bears. It is worth noting that, however, the estimated value and significance are lower in bears.

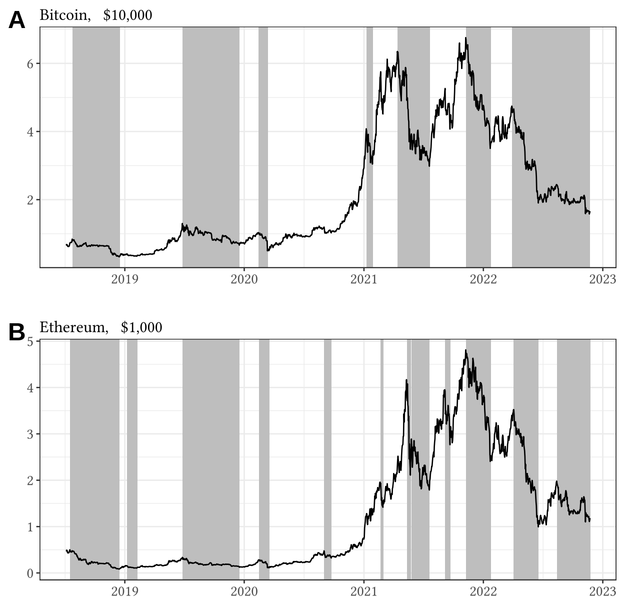

Figure B.1: Identification of bull and bear markets.
Grey background denotes detected bear periods. In Subplot (A) and (B), we use the price of Bitcoin and Ethereum as indices, respectively. The identification algorithm refers to Lunde and Timmermann (2004) with the corresponding amplitude thresholds set to 35% (bulls) and 25% (bears).

Robustness in subsamples: PoS tokens and DeFi tokens. As mentioned in the introduction, our model evolve both base layer pan-PoS staking mechanisms and higher layer DeFi stakable tokens. We model the common features and introduce several implications. In the empirical analysis, we use a sample containing the tokens from both the two layers. To empirically illustrate that these implications are common for both the pan-PoS and DeFi tokens, we divide our sample into two subsets based on the category of tokens, and repeat the main tests of Table 4.

Columns (9)-(12) of Table B.1 reports the results of these robustness tests. We regress pan-PoS and DeFi sub-samples on both daily and the weekly data sets. The dependent is log price change $r_{price_{i,t}}$ on the staking ratio in the previous week. The estimated coefficients of the staking ratio are both positive and consist with our main empirical result, which suggest that the staking ratio predicts price appreciation. The daily data shows both significant estimations, whereas in the weekly data, the statistical power is lower. This also consists with the main regression in Table

4. Also, it could be partly explained by the small sample size since the raw weekly sample set is further divided into two subsamples.

Discussion on the proxy of platform productivity. The platform productivity is captured by the average onchain transaction processing per second, denoted as $a_{i,t}$ in empirical tests. In practice, numerous platforms and blockchains aim to increase the transaction size of the flows processed on their chains, reflecting the platform productivity. Meanwhile, it is also influenced by the overall transaction needs, which means it does not necessarily to measure the hardware upper limits. However, both the two forces are closely related to the concept of transaction convenience and fit our main use for inducing platform productivity. Therefore, it is not necessary here to separate the two forces. Note that it may not capture the whole progress of platform development, such as transaction security and performance on specific financial services. It is beyond our scope to suggest an aggregated measurement.

Summary statics of crypto carry. Table B.2 summarizes the annualized carry and excess return of all tokens in our sample. Sample means and standard deviations are reported. We also include the US Dollar as one of the assets for which the carry and excess return are, by definition, equal to zero.

Crypto carry trade: long-only strategies. To compare with the benchmark of the equal weighted long strategy, also consider the potential short-selling restrictions, we test the performance of the long-only strategies as Figure B.2 shows. Since the market fluctuations are not hedged, all the strategies are volatile and move in co-trends. However, the strategy that goes long top 50% tokens with high carry still provide a relatively better performance with a larger Sharpe ratio as Table 7 reports in the main text.

Table B.1: Robustness test for Table 4: Staking ratio and token prices.

This table presents the robustness test on the analysis of how the staking ratio predicts token price appreciation. The regression model is the same as the one used in Column (2) of Table 4, in which the main independent is the staking ratio of the previous period, $StakingRatio_{i,t-1}$, and the dependent $r_{price_{i,t}}$ is the log price change. The difference is that we replicate the test on subsets of bulls, bears, PoS tokens, and DeFi tokens. The bulls and bears are detected based on Lunde and Timmermann (2004)'s algorithm. Due to the lack of a recognized index for the cryptocurrency market, we refer to the common approach used in practice, i.e. using the Bitcoin price as a market indicator. We also repeat with Ethereum as an indicator for robustness. The detected bulls and bears are visualized in Figure B.1. The subsets of pan-PoS and DeFi tokens are sorted based on tokens' nature. We also do the test in different horizons and with fixed effects to show the robustness of the results. Standard errors clustered in both token-specific and time dimensions are reported in parentheses. ***,**,* indicate statistical significance at the 1%, 5% and 10% respectively.

Dependent:	$r_{price_{i,t}}$											
	Bull-Bear								PoS-DeFi			
	Daily				7-Day				Daily		7-Day	
	Bitcoin as Indicator		Ethereum as Indicator		Bitcoin as Indicator		Ethereum as Indicator					
Sub-sample:	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	pan-PoS	DeFi	pan-PoS	DeFi
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$StakingRatio_{i,t-1}$	0.040***	0.010	0.025**	0.018	0.290***	0.017	0.135	0.124	0.028**	0.019*	0.143	0.167
	(0.009)	(0.012)	(0.011)	(0.012)	(0.098)	(0.094)	(0.091)	(0.109)	(0.012)	(0.010)	(0.107)	(0.097)
$\hat{\beta}_{i,t}$	-0.002	0.000	0.004	-0.011**	-0.051	-0.016	0.034	-0.169*	-0.003	-0.002	-0.016	-0.060
	(0.003)	(0.004)	(0.003)	(0.005)	(0.043)	(0.025)	(0.021)	(0.082)	(0.003)	(0.003)	(0.031)	(0.039)
$\log(Cap)_{i,t-1}$	-0.006***	-0.006***	-0.004***	-0.009***	-0.044***	-0.050***	-0.032***	-0.069***	-0.004***	-0.010***	-0.033***	-0.044*
	(0.002)	(0.002)	(0.001)	(0.003)	(0.012)	(0.016)	(0.008)	(0.020)	(0.001)	(0.002)	(0.009)	(0.023)
$r_{price_{i,t-1}}$	0.085*	-0.055	0.019	0.044	-0.116**	-0.004	-0.053	-0.195	0.066	0.098**	0.002	-0.112**
	(0.049)	(0.098)	(0.027)	(0.130)	(0.045)	(0.075)	(0.039)	(0.125)	(0.046)	(0.040)	(0.044)	(0.052)
$\Delta Network_{i,t-1}$	0.203***	0.353*	0.198***	0.412**	0.524	-0.284	0.421	-0.107	0.158***	0.259**	0.324	0.649**
	(0.062)	(0.178)	(0.065)	(0.190)	(0.314)	(0.332)	(0.262)	(0.357)	(0.047)	(0.111)	(0.343)	(0.290)
$a_{i,t-1}$	0.053	0.151	0.052*	0.114	0.448*	0.224	0.230	0.253	0.049	0.940***	0.276	1.145
	(0.035)	(0.116)	(0.027)	(0.121)	(0.245)	(0.771)	(0.198)	(0.895)	(0.044)	(0.227)	(0.317)	(2.280)
$Whale_{i,t-1}$	-0.018	0.006	-0.011	-0.011	-0.130	-0.107	-0.094	-0.141	-0.008	0.004	-0.073	-0.022
	(0.012)	(0.022)	(0.013)	(0.016)	(0.120)	(0.139)	(0.096)	(0.125)	(0.006)	(0.024)	(0.042)	(0.193)
$NotLaunched_{i,t}$	0.031***	0.001	0.021***	0.016	0.286***	0.075***	0.151***	0.270		0.006		0.142**
	(0.007)	(0.005)	(0.005)	(0.014)	(0.071)	(0.025)	(0.043)	(0.168)		(0.007)		(0.055)
$Y^0_{i,t}$	0.007*	0.007	0.005	0.012	0.078**	0.046	0.038	0.115	0.010*	0.007*	0.099**	0.079**
	(0.004)	(0.006)	(0.003)	(0.008)	(0.027)	(0.049)	(0.025)	(0.070)	(0.004)	(0.004)	(0.044)	(0.031)
Token FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,692	4,299	6,204	3,787	795	639	897	537	5,529	6,173	793	885
R^2	0.382	0.577	0.406	0.529	0.477	0.546	0.535	0.496	0.579	0.547	0.576	0.548

Table B.2: Excess return and carry.

Token	Excess Return (%, Annual)		Carry (%, Annual)		Token	Excess Return (%, Annual)		Carry (%, Annual)	
	Mean	Std.dev.	Mean	Std.dev.		Mean	Std.dev.	Mean	Std.dev.
0x	0.42	0.30	6.75	20.62	kusama	12.97	1.93	16.61	25.75
1inch	2.94	6.49	1.46	17.05	kyber	1.32	3.53	1.88	17.67
aave	3.83	0.98	6.21	21.56	livepeer	62.04	29.54	63.61	49.84
aion	6.25	3.01	8.86	18.61	lto	6.70	1.01	12.19	17.18
algorand	7.20	11.72	7.81	19.22	matic	17.78	14.01	25.23	40.64
ark	8.09	0.52	9.52	17.02	mina	10.32	2.81	9.60	20.97
avalanche	8.43	2.74	13.31	35.40	mirror	39.15	37.41	34.85	42.27
band	10.88	3.10	13.62	27.93	near	10.13	2.85	13.30	23.35
bifi	7.95	3.43	11.76	26.02	nem	−1.35	0.51	−1.59	14.28
binance-sc	8.02	6.38	9.05	15.10	neo	0.92	0.97	2.71	14.94
bitbay	1.13	0.98	10.62	63.06	nuls	8.31	0.56	10.67	16.96
cardano	4.39	2.77	6.52	17.95	oasis	11.80	4.55	12.95	26.77
celo	6.08	0.13	6.07	4.95	olympus	49.79	41.90	37.95	48.49
cosmos	9.82	2.35	11.97	18.55	osmosis	35.90	17.56	30.03	20.48
cronos	10.15	2.67	6.25	13.11	pancakeswap	74.76	26.66	78.13	51.65
curve	1.12	2.83	1.45	19.34	peakdefi	43.88	16.92	43.26	32.91
dash	5.20	0.73	7.28	26.50	polkadot	11.56	1.68	13.14	17.63
decred	5.58	1.71	6.66	14.32	qtum	4.73	1.31	6.30	14.07
dfinity	7.68	4.78	3.87	15.34	secret	24.47	3.95	27.70	28.47
dodo	56.63	10.73	50.54	22.66	smartcash	1.63	0.36	3.64	15.35
dydx	10.66	2.76	8.53	19.03	snx	21.96	23.54	26.42	37.33
elrond	14.24	7.45	19.18	32.93	solana	5.94	3.82	8.94	24.75
eos	10.69	12.06	11.02	18.81	stafi	18.76	4.02	19.91	27.21
eth2.0	8.61	10.82	11.45	18.44	stake-dao	22.23	8.32	21.49	19.43
fantom	27.83	23.95	37.98	47.03	sushi	10.51	10.12	8.85	20.06
flow	6.95	2.05	3.29	16.56	terra	8.26	3.71	14.26	35.66
harmony	8.58	2.89	12.42	27.40	tezos	4.56	2.11	5.52	16.99
icon	16.42	2.80	19.99	23.99	tron	2.81	1.94	4.36	13.99
idex	8.05	8.85	15.12	78.53	wanchain	7.39	0.26	9.44	16.86
injective	3.87	0.58	2.16	13.91	waves	3.84	1.62	6.21	22.75
iotex	8.86	3.14	11.27	21.23	wax	1.56	2.64	3.34	19.81
irisnet	9.67	0.38	14.77	22.07	yearn	14.51	16.78	16.86	30.14
kava	19.55	16.44	22.29	26.61	zcoin	15.02	3.77	18.35	16.90
US Dollar	0.00	0.00	0.00	0.00					

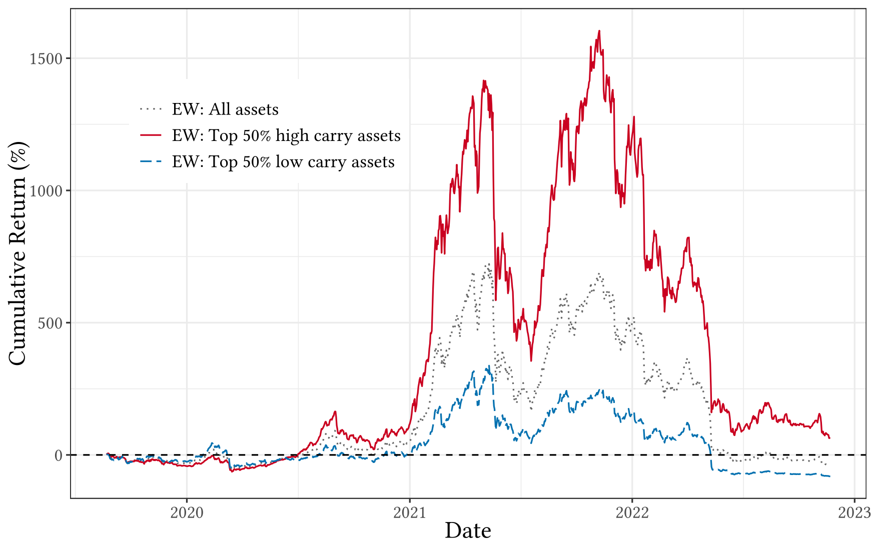

Figure B.2: Cumulative returns of long strategies.

This figure shows the cumulative returns of the following two strategies. The gray curve corresponds to the equal-weighted benchmark, i.e., borrow US dollar and long all the tokens with equal weight. The red curve shows the result of the top 50% EW strategy, that is, borrow US dollar and go long top 50% high carry tokens with equal weight. The blue curve shows the result of the lowest 50% EW strategy, i.e., borrow US dollar and go long the 50% tokens with the lowest carry with equal weight. The order of the tokens is evaluated every week.

Online Appendices for "The Tokenomics of Staking"

OA1 Institutional Background of Staking

OA1.1 Staking Mechanisms

Blockchain-based staking in general involves two broad categories of activities: those related to pan-PoS consensus protocols and those in higher layer DeFi applications.[32] Even on non-blockchain-based or centralized platforms, various programs that involve escrows or crowd funds can be analyzed as a form of business layer staking through the lens of our framework. Fundamentally, a blockchain functions to generate a relatively decentralized consensus record of system states to facilitate economic interactions such as value or information exchanges (e.g., Cong and He, 2019). PoS protocols have gained popularity and momentum with major market players such as Ethereum adopting them. Under PoS, agents stake native tokens to compete for the opportunity to record transactions, execute smart contracts, append blocks, etc., to earn block rewards and fees. Meanwhile, various staking programs have become popular means to encourage desirable behavior in higher layer applications, escrowing a balance of tokens under custody in a smart contract, or deploy them to enable network economic functionalities.

Consensus generation in PoS. Fundamentally, blockchain functions to generate a relatively decentralized consensus to enable economic interactions such as value or information exchanges (e.g., Cong and He, 2019). Permissionless blockchains have historically relied on variants of the PoW protocol. Because of scalability and environmental issues of PoW (Cong, He, and Li, 2021; John, Rivera, and Saleh, 2020), PoS protocols have gained popularity and momentum for both permissioned and permissionless blockchains, with major market players adopting and incumbents such as Ethereum contemplating a conversion (Irresberger et al., 2021).

Under PoS, agents who stake native tokens have the opportunity to append blocks and earn block rewards and fees as compensation. The more one stakes, the more likely one is to be selected and compensated for their participation (Saleh, 2021, contains more details). Note that holding a token does not necessarily mean participating in staking. In practice, agents incur negligible physical costs (as opposed to the high entry cost of PoW mining or directly maintaining a node

[32] The two are not mutually exclusive. Solana, for example, uses both PoS and DeFi staking. The classification we use follows mainstream cryptocurrency data aggregators such as CoinMarketCap.

in PoS). Our study includes all protocols using pan-PoS protocols, such as Proof-of-Credit (POC) used in Nuls, which are variants of the above mechanisms. Online Appendix OA1 provides more background information and examples in practice.

Staking in DeFi. Staking programs are a popular means for incentivizing desirable behavior and guarding against misbehavior in DeFi applications. It escrows a balance of tokens under custody in a smart contract and stakers receive rewards similar to interest payments from their tokens staked (Harvey, Ramachandran, and Santoro, 2021). Synthetix is an example of an open-source DeFi protocol with staking where users can create and trade derivative tokens and gain exposure to assets like gold, bitcoin, and euros without having to actually own them. These derivative assets are collateralized by the platform tokens (SNX) which, when locked in the contracts, enables their issuance. In return, SNX stakers earn rewards from both newly issued tokens and small fees transactions generate.[33] Another salient form of staking is yield farming, which allows investors to earn yield by temporarily locking tokens in a decentralized application (dApps). Yield farming often entails shorter lock-up (some allows withdrawal at any time), uncertain yields, and higher risks. (see, Augustin, Chen-Zhang, and Shin, 2022, for more institutional details).

Without getting bogged down with specific eligibility requirements and operational differences across various DeFi protocols and smart contracts, DeFi staking can be characterized as simply earning rewards by collateralizing the tokens for some functionalities in the network.

Reward determination and slashing. In most staking programs, the total rewards used to incentivize staking or its determination mechanism are pre-specified and announced. In PoS, the blockchain branch is randomly selected from the whole staking pool. Then the staking reward is randomly distributed to stakeholders based on the number of staked coins they hold as a probability weight.[34] Similarly, on DeFi platforms, stakers share the rewards from transaction fees or predetermined emissions (minting of new tokens).

Staking reward rate can be naturally compared to interest rate or yield of other financial assets. However, unlike deposit rates set by the banks, staking reward rate is jointly determined by

[33] DeFi staking may involve multiple tokens. For example, in MakerDAO, the profits generated from DAI can be viewed as a yield on ETH staking, and our framework can be used to understand the price impact on ETH.

[34] For example, if an investor stakes 10 coins while the aggregate staked amount of this branch is 100, then the investor has a 10% probability of appending to the branch and receiving the staking reward.

the announced staking reward and the aggregate tokens staked. Online Appendix OA1 details the staking programs for the tokens in our sample. Stakers face the risk of losing the staked tokens due to possible security attacks, illegal verification, and storage failures. To discourage the misbehavior of the validator, most projects also propose a punishment mechanism known as *slashing*. A pre-defined percentage of a validator's tokens are lost when it does not behave consistently or as expected on the network (e.g., downtime and double signing).

Market and information. In PoS, validators compete in the amount of staking to earn rewards. To incentivize more delegates, they develop a reward distribution plan at the node level. Potential delegates can freely choose among these nodes or delegate through some intermediaries. Therefore, nodes engage in price competition for delegated stakes. For DeFi platforms, staking reward rates are typically equal for participants, but some white-listed groups may have priority in staking. Most stakable tokens are launched on mainstream cryptocurrency exchanges. Investors can easily invest in these staking projects and trade these tokens with cryptocurrency assets such as Bitcoin and Ethereum.

Information on staking programs, including participation rules, reward distribution plan, total staked value (or total value locked, TVL, which includes non-native tokens), and even information of all the validators, are open and can be easily obtained on official websites of projects. Third-party websites also specialize in collecting real-time information on staking projects, e.g., *Stakingrewards.com*. In particular, the *staking ratio*, which captures the total number of tokens staked as a fraction of the total number of tokens, is typically public knowledge.

OA1.2 Forms of Staking in Our Sample

PoS staking. Under PoS, agents who stake native tokens have opportunities to append blocks and earn block rewards and fees as compensation. There are mainly two ways to participate. The first is to *run a validator node, staking pool, or masternode* by holding native tokens and incurring the costs including hardware costs and time spent on maintenance. The more one stakes, the more likely one is to be selected and compensated for their participation(Saleh, 2021, contains more details). Note that holding a token does not necessarily mean participating in staking. The second way is through *delegation*. Agents only need to delegate their tokens to an existing node or a pool to receive a reward earned by the node/pool. This route is flexible and friendly for players with fewer tokens and allows them to share risk (Cong, He, and Li, 2021). In practice, agents incur negligible physical costs (as opposed to the high entry cost of PoW mining or directly maintaining a node in PoS).

Solana is a concrete example of pan-PoS staking.[35] Solana is an open-source project that implements a new, high performance, permissionless blockchain. It enables transactions to be ordered as they enter the network, rather than by block, which makes Solana one of the fastest blockchains in the world and the rapidly growing ecosystem in crypto, with thousands of projects spanning DeFi, NFTs, Web 3.0 and more. Solana uses Proof-of-Stake (PoS) as its consensus mechanism. The performance is improved by its innovative protocol, Proof-of-History (PoH). Solana's Proof-of-Stake is designed to quickly confirm the current sequence of transactions produced by the PoH generator, vote and select the next PoH generator, and punish misbehaving validators. A block in the context of Solana is simply the term used to describe the sequence of entries that validators vote on to achieve confirmation. *Validators* within Solana's PoS consensus model are the entities responsible for confirming if these entries are valid. *SOL* is the name of Solana's native token, which can be passed to nodes in a Solana cluster in exchange for running an on-chain program or validating its output. *Stakers* delegate SOL to validators to help increase these validators' voting weight. Such action indicates a degree of trust in the validators. Stakers delegate to ensure validators cast honest votes and hence ensure the security of the network. The more stake delegated to a validator, the more often this validator is chosen to write new transactions to the ledger, and then the more *rewards* the validator and its delegators earn.

Staking DeFi native tokens. Incentivizing desirable behavior and guarding against misbehavior are crucial in DeFi applications. To this end, staking programs are popular and important in practice, which applies to a balance of tokens under custody in a smart contract. Users on DeFi platforms receive staking rewards as a form of interest payment from their token balance staked (Harvey, Ramachandran, and Santoro, 2021).

In practice, DeFi staking may involve different lock-up periods and multiple tokens.[36] The risks of being slashed and losing the staked tokens are also different. Without getting bogged down with specific threshold requirements and operational differences across various DeFi protocols and smart contracts, DeFi staking can be characterized as simply earning rewards by col-

[35]For references, see https://docs.solana.com, *blockdaemon.com*, and https://blockdaemon.com/platform/validator-node/how-solana-staking-works/.

[36]MakerDAO is a good example. The profits generated from DAI can be viewed as a yield on ETH staking, and our framework can be used to understand the price impact on ETH.

lateralizing the tokens for some functionalities in the network. From the stakers' perspective, staking shares the spirit of certificates of deposit or risky illiquid investments.

Transaction gas fees and Rewards. We summarize the gas fee foundations of Ethereum (EIP 1559) as an example. The major of contents are extracted from the official webpage of Ethereum and the third-party page, *blocknative*.[37]

Gas refers to the unit that measures the amount of computational effort required to execute specific operations on the Ethereum network. Since each Ethereum transaction requires computational resources to execute, each transaction requires a fee. Gas thus refers to the fee required to execute a transaction on Ethereum.

Every block has a *base fee* which acts as a reserve price. To be eligible for inclusion in a block the offered price per gas must at least equal the base fee. The base fee is calculated independently of the current block and is instead determined by the blocks before it - making transaction fees more predictable for users. When the block is mined this base fee is "burned", removing it from circulation. The base fee is calculated by a formula that compares the size of the previous block (the amount of gas used for all the transactions) with the target size. The base fee will increase by a maximum of 12.5% per block if the target block size is exceeded. This exponential growth makes it economically non-viable for block size to remain high indefinitely.

In origin, miners would receive the total gas fee from any transaction included in a block. With the new base fee getting burned, the London Upgrade introduced a *priority fee* (tip) to incentivize miners to include a transaction in the block. Without tips, miners would find it economically viable to mine empty blocks, as they would receive the same block reward. Under normal conditions, a small tip provides miners a minimal incentive to include a transaction. For transactions that need to get preferentially executed ahead of other transactions in the same block, a higher tip will be necessary to attempt to outbid competing transactions.

Staking rewards are the combination of gas fees and the emission of new tokens. Together with the gas fee policies summarized above, as well as the mechanism of rewards from emission described in the main text, the main take-away is that the reward distribution design is widely under the platform's control, whereas the crowd decisions and interactions provide influence under the designed structure. In practice, the staking rewards may also involve the phenomenon

[37] Please see https://ethereum.org/en/developers/docs/gas/, and https://www.blocknative.com/blog/eip-1559-fees, respectively.

of multilevel distribution, as some agents can delegate tokens to larger nodes. The holders of the larger nodes thus need to have a process for deciding on the distribution of benefits. Therefore, there may exist multiple staking participation methods for one token. In relevant empirical tests, we always choose the participation method with the lowest capital threshold and risk, such as delegating, voting, etc.

Examples in practice. We summarize representative staking programs involving tokens in our sample. Most information is accessed from *Stakingrewards.com.* There is also information from official websites of corresponding tokens. Many tokens have similar mechanisms, thus we do not repeat the description. These descriptions are excerpted in 2022. There may be changes over time in the specific mechanisms of some programs, whereas these descriptions apply to the time intervals covered by the data in our paper.

- The individual AION rewards depends on the Block Reward, Block Time, Daily Network Rewards and Total Staked. Every block one validator is randomly selected to create a block, whereas 1 staked or delegated token counts as one "lottery ticket". The selected validator has the right to create a new block and broadcast them to the network. The Validator then receives the 50% of the block reward and the fees of all transactions (network rewards) successfully included in this block, whereas the PoW Miner receives the other 50%.
- Rewards in the form of algos are granted to Algorand users for a variety of purposes. Initially, for every block that is minted, every user in Algorand receives an amount of rewards proportional to their stake in order to establish a large user base and distribute stake among many parties. As the network evolves, the Algorand Foundation will introduce additional rewards in order to promote behavior that strengthens the network, such as running nodes and proposing blocks.
- The individual BitBay rewards depends on the Block Reward, Block Time, Daily Network Rewards and Total Staked. Every block is randomly selected whereas 1 staked coin counts as one "lottery ticket". The selected staker has the right to create a new block and broadcast it to the network. He then receives the block reward and the fees of all transactions successfully included in this block.
- Dash blockchain consensus is achieved via Proof of Work + Masternodes. Investors can

leverage their crypto via operating masternodes. Miners are rewarded for securing the blockchain and masternodes are rewarded for validating, storing and serving the blockchain to users.

- Eos has a fixed 5% annual inflation. 4% goes to a savings fund, which might distribute the funds to the community later on. 1% goes to Block producers and Standby Block Producers. Out of the 1% that are given to block producers, only 0.25% will go to the actual 21 producers of the blocks. The other 0.75% will be shared among all block producers and standby block producers based on how many votes they receive and with a minimum of 100 EOS/day.
- The individual reward of staking fantom depends on the Total Staked ratio. Transactions are packaged into event blocks. In order for event blocks to achieve finality, event blocks are passed between validator nodes that represent at least 2/3rds of the total validating power of the network. A validator's total validating power is primarily determined by the number of tokens staked and delegated to it. A validator earns rewards each epoch for each event block signed according to it's validating power. By delegating, investors can increase the share of their validator proportionally to the balance of their account. They will receive rewards accordingly and share them with investors after taking the commission.
- The effective yield for staking IDEX depends on the actual Trading Volume on IDEX Market. The higher the trading volume on IDEX, the higher are the actual rewards. The second metric to watch is the total amount of AURA currently staking. Fewer tokens on stake result in higher rewards.
- Every livepeer (LPT) token holder has the right to delegate their tokens to an Orchestrator node for the right to receive both inflationary rewards in LPT and fees denominated in ETH from work completed by that node.
- The individual LTO rewards depends on the Network Rewards (Transaction Fees spent on the Network) and the Total Staked. Every block one staking node operator is randomly selected to create a new block, whereas 1 staked token counts as one "lottery ticket". The staker receives the fees of all transactions successfully included in this block. Staking Node Operators share the rewards with their delegators after deducting a commission.

- NEM blockchain consensus is achieved via Proof of Importance. Investors can leverage their crypto via harvesting. To harvest NEM coins it is recommended to run the official NEM Core wallet with an entire copy of the blockchain on the stakers' computer or a Virtual Private Server (VPS). The individual NEM harvesting rewards depends on the Daily Network Rewards and Total Staked. For every block, the staker is randomly selected whereas 1 staked coin counts as one "lottery ticket". The selected staker has the right to create a new block and broadcast it to the network. The staker then receives the fees of all transactions successfully included in this block.

- Everyone who holds NEO will automatically be rewarded by GAS. GAS is produced with each new block. In the first year, each new block generates 8 GAS, and then decreases every year until each block generates 1 GAS. This generation mechanism will be maintained until the total amount of GAS reaches 100 million and no new GAS will be generated.

- Nuls blockchain consensus is achieved via Proof of Stake + Masternodes. Investors can leverage their crypto via staking. The amount earned is variable based on the current blockchain metrics like the amount of stakers (Total Staked ratio). Investors can stake Nuls into a project's nodes and earn their token as a reward, while the project earns Nuls as a reward. Some projects offer to stake with just 5 Nuls as the minimum.

- Delegators in Polkadot are called Nominators. Anyone can nominate up to 16 validators, who share rewards if they are elected into the active validators set. The process is a single-click operation inside the wallet. The current reward rate for validators is determined by the current Total Staked ratio. The less DOT is being staked, the higher are the rewards.

- Qtum blockchain consensus is achieved via Proof of Stake 3.0. The individual reward depends on the Block Reward, Block Time, Daily Network Rewards and Total Staked. Every block is randomly selected whereas 1 staked coin counts as one "lottery ticket". The selected staker has the right to create a new block and broadcast it to the network. The staker then receives the block reward and the fees of all transactions successfully included in this block.

- Synthetix Network Token blockchain consensus is achieved via the Ethereum Blockchain. Investors can leverage their crypto via staking. SNX holders can lock their SNX as collateral to stake the system. Synths are minted into the market against the value of the locked SNX, where they can be used for a variety of purposes including trading and remittance. All Synth trades on Synthetix Exchange generate fees that are distributed to SNX holders, rewarding them for staking the system.

- Tezos blockchain consensus is achieved via Liquid Proof of Stake. Investors can leverage their crypto via baking or delegating. There are a number of tokens that use a similar mechanism, including iotex, irisnet, etc.

- Tron reward depends on the Block Rewards, Endorsement Rewards, Block Time, Daily Network Rewards and Total Staked. Every block is randomly selected to bake a block and 32 stakers are selected to endorse a block, whereas 1 staked coin counts as one "lottery ticket". The selected stakers have the right to create or endorse new block and broadcast them network. The Baker then receives the block reward and the fees of all transactions successfully included in this block. The Endorsers receive the endorsement rewards.

- Wanchain blockchain consensus is achieved via Galaxy Proof-of-Stake. The individual WAN rewards depends on the Foundation Rewards, Daily Network Rewards and Total Staked. At the beginning of each protocol cycle (epoch), two groups, the RNP (Random Number Proposer) group and the EL (Epoch Leader) group, are selected from all validators. 1 staked or delegated token counts as one "lottery ticket" to be selected. The two groups equally share the Foundation Rewards and Transaction Fees (Network Rewards). The Foundation Rewards consists of 10% of the outstanding Wanchain Token Supply and are decreasing by 13.6% each year, whereas the Network Rewards are expected to rise alongside wider network usage.