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Does what happens on-chain stays on-chain? The dynamics of blockchain token transactions and prices[☆]

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A R T I C L E I N F O

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A B S T R A C T

Cryptoassets, particularly tokens, have garnered investor interest due to high returns, yet comprehensive studies examining on-chain transaction data to assess their intrinsic value remain limited. This study addresses this gap by introducing new on-chain transaction-based measures of token usage, crypto-exchange supply pressures, and aggregate transaction intention (trading versus usage/holding). Using over 180 million records of Ethereum-based-tokens' transaction data, we categorize on-chain transactions as peer-to-peer usage or crypto-exchange-related. Our findings show that while increased token usage intensity, whether through peer-to-peer or exchange transactions, positively correlates with higher token returns, imbalances in exchange flows have the opposite effect. Specifically, increased token inflows to exchanges signal potential supply pressure and increased token deposits signal aggregate intention to trade, both contributing to price declines. This research underscores on-chain data as a reliable economic signal and its impact on token valuations.

1. Introduction

Cryptoassets have rapidly positioned themselves as a transformative element in global finance, challenging conventional financial structures and drawing increasing interest from investors, scholars, and regulators (Corbet et al., 2019; Urquhart and Yarovaya, 2023). In response to this growing relevance, researchers have developed a variety of models to explain cryptoasset valuation, ranging from adaptations of traditional equity valuation frameworks to approaches that incorporate cryptoasset-specific features and blockchain-based functionalities (Athey et al., 2016; Abadi and Brunnermeier, 2018; Biais et al., 2019; Schilling and Uhlig, 2019; Shams, 2020; Shen et al, 2020; Cong et al., 2021; Huberman et al., 2021; Liu and Tsyvinski, 2021; Saleh, 2021; Ciner et al., 2022; Cong et al., 2022; Liu et al., 2022; Shen et al., 2022; Lucey et al., 2022; Yousaf and Yarovaya, 2022a, 2022b; Sockin and Xiong, 2023; Sakkas and Urquhart, 2024; Prat et al., 2025).

Within the broader crypto-asset landscape, tokens represent a specialized subset typically designed to serve distinct functions within their respective ecosystems (Benedetti et al., 2023). These functions range from incentivizing participation and enabling tokenized data exchange (e.g., Ocean Protocol – OCEAN[1]), facilitating decentralized governance and real-world event reporting (e.g.,

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[1] https://coinmarketcap.com/currencies/ocean-protocol/#About.

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Augur – REP[2]), enabling transparent dispute resolution (e.g., Kleros – PNK[3]), enhancing cybersecurity through decentralized threat detection (e.g., PolySwarm – NCT[4]), and improving efficiency in global trade and supply chain document transfers (e.g., CargoX – CXO[5]). These tokens, which are part of our dataset, illustrate the diverse functionalities that tokens can serve within blockchain ecosystems.

Despite these functionalities within blockchain ecosystems, tokens are often perceived primarily as speculative instruments, a view that tends to overlook the intrinsic value generated through their actual use by participants (Grobys and Junttila, 2021; Bonaparte, 2022; Haykir and Yagli, 2022; King and Koutmos, 2024). In contrast, we hypothesize that greater intensity of token usage within an ecosystem contributes to the expansion and reinforcement of network effects (Katz and Shapiro, 1985; Katz and Shapiro, 1986; Katz and Shapiro, 1994), where increased participation enhances the token's utility and, consequently, its perceived value. As users engage in peer-to-peer transactions or access ecosystem services through tokens, such activity may increase the robustness and attractiveness of the platform, stimulating further demand. This study explores whether such usage-driven dynamics are reflected in market valuations by examining the empirical relationship between token usage intensity and token returns.

A second focus is on the influence of exchange-related transactions on token valuations. This analysis explores the potential impact of imbalances in token inflows and outflows, which may indicate shifts in market pressures, as well as the imbalance between deposit and withdrawal transactions, which may signal changes in users' aggregate intention to trade tokens.

A distinctive feature of blockchain-based assets is that their transaction histories are permanently recorded on-chain, creating an immutable and transparent ledger of activity. These on-chain transactions offer publicly accessible, tamper-resistant data that reveal detailed patterns of user behavior, including token transfers, deposit and withdrawal flows, and peer-to-peer interactions. While a limited number of studies have begun to explore the informational value of on-chain data (Foley et al., 2019; Griffin and Shams, 2020; Benedetti and Nikbakht, 2021; Lyandres et al., 2022), this literature remains sparse, and most research continues to rely on off-chain indicators or aggregate market data.

Despite these early efforts, transaction-level on-chain data remains underutilized in the empirical literature on token valuation, particularly in distinguishing functional usage from speculative trading activity. This study addresses that gap by leveraging on-chain information to distinguish between functional peer-to-peer usage and speculative or exchange-driven trading activity. Specifically, we examine how on-chain user behavior contributes to market microstructure, conveys transaction intent, and ultimately influences token returns. By analyzing how these observable signals affect tokens' prices, our research aims to deepen the understanding of information flow, liquidity pressures, and price formation mechanisms within token markets.

We propose new measures to quantify token usage intensity based on publicly observable on-chain transactions. To this end, we categorize on-chain transactions into two groups: (i) peer-to-peer transactions (referred to as "token usage" transactions) as presented in Fig. 1, or (ii) exchange-related transactions on centralized and decentralized platforms (referred to as "CeDex transactions") as presented in Fig. 2. This categorization allows to analyze participants behavior, in particular, how interactions between peers or with exchanges—whether centralized or decentralized[6]— affect token prices. Peer to peer transactions often reflect functional use within a blockchain ecosystem whereas CeDex or exchange-related transactions often reflect trading or speculative activity.

Building on insights from our classification of on-chain transactions, we develop a series of hypotheses to examine the relationships between token usage intensity, exchange-related activities, and their combined impact on market prices. Our analysis begins by examining whether increased token usage, both in transaction count and volume, is positively associated with higher token prices. Specifically, we test if increased peer-to-peer transactions (H1: Peer Usage Hypothesis) and exchange-related transactions (H2: Exchange-Related Transaction Hypothesis) each contribute to an increase in market value. Next, we investigate the effects of imbalances in transaction behavior to and from exchanges. This includes assessing whether a greater volume of tokens moving into exchanges, relative to those leaving, signals supply imbalance and potentially decreases prices (H3: Market Supply Pressure Hypothesis); and whether a higher number of deposit transactions (compared to withdrawals) reflects a stronger aggregate market intention to trade rather than to use/hold tokens, which may indicate bearish expectations and exert downward pressure on prices (H4: Aggregate Market Intention Hypothesis).

Theoretical models on token valuation (Cong et al., 2021, 2022; Malinova and Park, 2023; Prat et al., 2025; Sockin and Xiong, 2023) emphasize the importance of distinguishing between transactional and functional usage demand versus investor speculative demand when assessing token value. This distinction is crucial, as speculative token transactions do not necessarily indicate active usage or contribute to the intrinsic value derived from a token's intended function within its ecosystem. By differentiating between speculative transactions and functional usage, our study provides a more nuanced understanding of token usage and its impact on market valuation.

To test our hypotheses, we construct a dataset of blockchain transactions and secondary market information for all Ethereum-based tokens with identifiable contract addresses listed on CoinMarketCap.com,[7] resulting in a set of 512 tokens. Our blockchain transaction

[2] https://coinmarketcap.com/currencies/augur/#About.

[3] https://coinmarketcap.com/currencies/kleros/#About.

[4] https://coinmarketcap.com/currencies/polyswarm/#About.

[5] https://coinmarketcap.com/es/currencies/cargox/#About.

[6] Centralized exchanges (CEX) are platforms where trades are facilitated by a central group of entity (i.e.: Binance, Coinbase, etc.), whereas decentralized exchanges (DEX) are smart-contract based protocols that allow peer-to-peer trading without intermediaries (i.e.: Uniswap).

[7] Coinmarketcap.com is a leading data provider for cryptoassets, with indices featured by NASDAQ, Bloomberg Terminal, Thomson Reuters, and others.

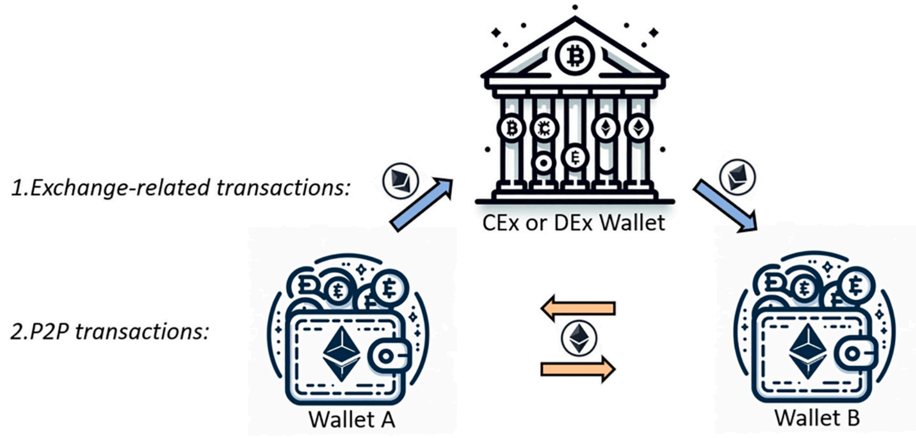

Fig. 1. On-chain transactions diagram (Types of transactions):

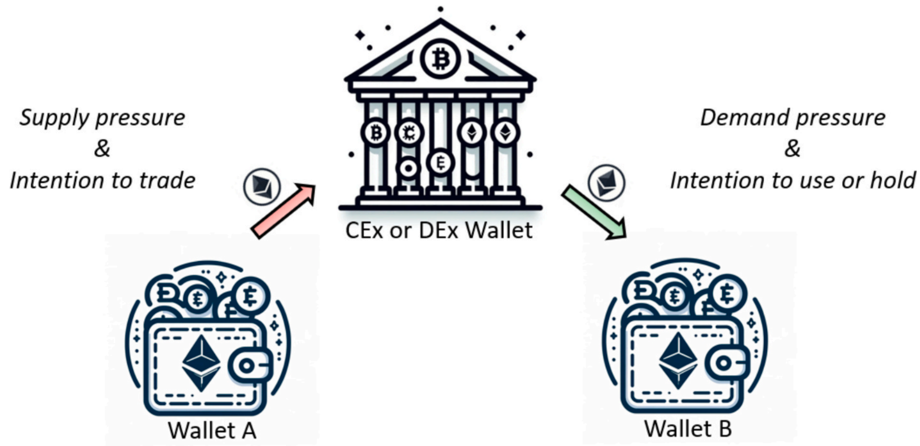

Fig. 2. Exchange-related transactions.

dataset, sourced from Etherscan.io,[8] spans from each token's creation date to June 10, 2021, capturing over 180 million individual transactions. Each transaction record includes the transaction address, sender and receiver addresses, transaction timestamp, and token quantity transferred. While Ethereum was launched on July 30, 2015, tokens on the Ethereum blockchain are created at different points in time, and some perform blockchain transactions before they begin trading in secondary markets. Secondary market information, including daily price and trading volume, is gathered from CoinMarketCap.com, covering each token's first available trading day until June 10, 2021.

To distinguish peer-to-peer from exchange-related activity, we identify wallet addresses belonging to centralized and decentralized exchanges following the methodology outlined by Foley et al. (2019), resulting in a list of 2,320 unique addresses. Transactions involving an exchange wallet as either sender or receiver are classified as CeDex transactions, while all other transactions are classified as peer-to-peer. Several studies have empirically analyzed token adoption and network growth by tracking the number of blockchain wallets with positive token balances or transaction volumes (e.g., Benedetti and Nikbakht, 2021; Lyandres et al., 2022). However, traditional wallet-count measures do not fully capture usage intensity or distinguish between speculative holdings and active token use.

We examine how token-specific on-chain transaction information contributes to explaining the unexplained returns of cryptocurrency tokens through a two-step methodology that analyzes both the common and token-specific pricing factors. Among the common pricing factors we include cryptoasset market return, asset return volatility, Amihud illiquidity ratio, and market trading volume. First, we estimate each token's abnormal return using a market model with the Bloomberg's Galaxy Crypto Index (BGCI) return as market return and the US 10 years government bond daily yield as the risk-free rate. On a second step, we explore whether

[8] Etherscan.io is a leading blockchain explorer that provides information on Ethereum Blockchain blocks and on every transaction from Ethereum-based tokens (https://etherscan.io/).

token-specific factors (such as off-chain trading volume) and our proposed on-chain-based measures of usage intensity, CeDex supply imbalance, and aggregate intention, can explain these residuals. By incorporating controls for market conditions and addressing time-series effects, this methodology enables us to distinguish the effects of token usage transactions and trading-related transactions, shedding light on the economic signals conveyed through on-chain activity.

Our analysis offers nuanced insights into the drivers of token prices in crypto markets. First, we find that token usage intensity—whether through peer-to-peer or exchange-related transactions—significantly increases market valuation, supporting the hypotheses that increased usage (whether functional or transactional) correlates with higher token returns (H1 and H2). This reinforces the view that token adoption and demand stemming from network effects, positively impact token prices. In contrast, our examination of exchange flow imbalances reveals a different influence on valuation. Specifically, an increase in the volume of tokens moving into exchanges relative to outflows (supply pressure) correlates with price declines (H3), as does a higher number of transactions into exchanges compared to outflows, reflecting higher aggregate intention to trade rather than higher intention to use/hold tokens (H4). These findings underscore the role of publicly observable on-chain metrics, such as transaction volume and flow direction, in shaping market dynamics and capturing shifts in supply and demand, which, in turn, drive token valuations. Our findings reveal that on-chain transactions serve as reliable economic signals within token markets. Their transparent, observable nature makes them valuable indicators of market conditions and aggregate intentions.

Our study underscores the complexity of factors driving crypto asset prices, in particular tokens, revealing layers that go beyond traditional market theories. By unpacking these relationships, our research advances both academic discourse and practical understanding, offering insights for investors, market regulators, and other stakeholders. Our findings provide a foundation for future studies to explore the intricacies of token markets, with potential implications for refined investment strategies and regulatory frameworks.

The structure of the paper is organized as follows: Section 2 presents a review of current literature and the theoretical background, situating our hypotheses within existing research on cryptoasset markets. Section 3 describes the data and our proposed measures for peer-to-peer usage, exchange-related transactions, market supply pressure, and aggregate market intention. Section 4 describes the estimation methodology, presents our results and provides robustness checks. We conclude with Section 5, which provides closing remarks and outlines future research directions in this dynamic field.

2. Literature review and hypotheses development

2.1. Cryptoasset Valuation: Theoretical and empirical Perspectives

Cryptoassets have gained significant attention in recent years, with many investors attracted to their potential for high returns. Researchers have similarly focused on understanding the factors driving cryptoasset returns, with some studies adapting traditional equity valuation methods and others incorporating blockchain-specific factors (Corbet et al., 2019; Urquhart and Yarovaya, 2023). A broad literature has developed theoretical models for cryptocurrency valuation (Abadi and Brunnermeier, 2018; Biais et al., 2019; Schilling and Uhlig, 2019; Shams, 2020; Huberman et al. 2021; Liu and Tsyvinski, 2021; Saleh, 2021; Sockin and Xiong, 2023), others have developed theoretical frameworks for the fundamental valuation of utility tokens and platform-specific currencies (Cong et al., 2021; Cong et al., 2022; Prat et al., 2025), analyzing how utility tokens can reduce monopolistic rent-seeking behavior on digital platforms (Goldstein et al., 2024). Other studies examine cryptocurrency behavior during periods of market turbulence, such as arbitrage opportunities (Makarov and Schoar, 2020; Duan et al., 2024), speculative bubbles and crashes (Cheah and Fry, 2015; Corbet et al., 2018; Yousaf and Yarovaya, 2022a, 2022b; Dai et al., 2023; Chen et al., 2024), pump-and-dump schemes (Dhawan and Putniņš, 2023; Li et al., 2023), global events (Polyzos and Youssef, 2025), and token or stablecoin issuance events (Griffin and Shams, 2020; Howell et al., 2020; Benedetti and Kostovetsky, 2021).

There is an ongoing debate regarding the predictability of cryptocurrency returns. While some argue that cryptocurrency prices follow a martingale and are thus unpredictable (e.g., Schilling and Uhlig, 2019), others suggest that dynamic valuation models may allow returns to be forecasted based on both traditional and crypto-specific factors (Shams, 2020; Liu and Tsyvinski, 2022; Sockin and Xiong, 2023). Traditional equity models used in cryptocurrency research focus on factors like momentum, book-to-market ratios, investor attention and sentiment, valuation metrics, and correlations with conventional asset markets, including commodities, stocks, currencies, and macroeconomic indicators (Athey et al., 2016; Schilling and Uhlig, 2019; Shen et al., 2020; Liu and Tsyvinski, 2022; Ciner et al., 2022; Lucey et al., 2022; Shen et al., 2022; Yousaf and Yarovaya, 2022a, 2022b). Other studies focus on cryptocurrency-specific factors such as production and computing costs, as well as network metrics (Sockin and Xiong, 2023), though some find no empirical link between production costs and returns (Liu and Tsyvinski, 2022). A number of studies have focused on ICOs or initial coin offerings (Adhami et al., 2018; Bakos and Halaburda, 2018; Catalini and Gans, 2018; Canidio, 2020; Howell et al., 2020; Benedetti and Kostovetsky, 2021; Chod and Lyandres, 2021; Gryglewicz et al., 2021; Garratt and van Oordt, 2022; Hege et al., 2022). Finally, several studies examine the impact of news and market sentiment on cryptocurrency returns. Bleher and Dimpfl (2019) analyze Google search volumes as predictors of volatility in major cryptocurrencies, finding evidence of volatility predictability but not return predictability. Liu and Tsyvinski (2021) approximate market sentiment using investor attention proxies from Google searches, social media, and news, discovering that high attention predicts positive future returns while negative attention forecasts cumulative declines. Lee and Jeong (2023) examine the influence of information excess on the volatility of cryptocurrencies. Wu et al. (2025) study attention spillovers in cryptocurrencies using Goggle Trends as proxy for attention and propose an attention-enhanced portfolio strategy. Other studies leverage sentiment derived from news sources (Rognone et al., 2020; Sapkota, 2022), tweets (Polyzos et al., 2024), social media (Guégan and Renault, 2021) and music sentiment (Hadhri et al., 2025) to assess their influence on cryptocurrency returns, trading volume, and volatility.

2.2. Token utility, network effects, and life cycle theories

Among these factors, token adoption and network effects (Katz and Shapiro, 1985; Katz and Shapiro, 1986; Katz and Shapiro, 1994) stand out as central to cryptocurrency valuation, as demand from both users and developers can drive value through community expansion. Research on cryptocurrency adoption and network effects highlights their positive influence on prices (Biais et al., 2019; Cong et al., 2021; Cong et al., 2022; Pagnotta, 2022; Sakkas and Urquhart, 2024). Buying pressure from investors seeking to hold tokens can amplify perceived adoption and utility, enhancing demand beyond mere speculation (Gandal and Halaburda, 2016; Shams, 2020; Cong et al., 2021; Cong et al., 2022; Halaburda et al., 2022; Sockin and Xiong, 2023; Li and Mann, 2025). These network effects and community adoption measures are often proxied by metrics like active users, addresses, and transaction volumes on networks such as Ethereum, which have been shown to positively correlate with token valuations (Benedetti and Nikbakht, 2021; Lyandres et al., 2022). New theoretical models develop life-cycle token phases theories in which the dual role of tokens are associated; phases in which tokens are viewed as speculative assets for financial investors, and phases in which tokens represent means of transactions for users (Mayer, 2022; Prat et al., 2025). In particular, Prat et al. (2025) differentiate two phases in their theoretical model; early speculative token phase and mature adoption token phase. They empirically calibrate the model using 3 utility tokens: Ethereum, Maker and Link tokens. Compared to Cong et al. (2021), which pioneered the term "tokenomics" and assumes users derive utility from merely holding tokens or "staking", the theoretical model purposed by Prat et al. (2025) enforces actual exchange for services (utility), using for this purpose the proxy "velocity of circulation" as the ratio of gas fees over token supply. They show that token usage behavior is more present than speculative behavior in a second mature adoption phase, and the model predicts that this behavior is positively correlated with token price.

2.3. Hypotheses development

Our paper continues with this string of literature, empirically focusing on the above-mentioned second phase, once the tokens are in a mature phase and become listed in cryptoexchanges (either centralized or decentralized). In this study, we introduce a more direct approach to testing token-usage intensity, supply pressure, and aggregate transaction intention in token markets by analyzing data from public on-chain transactions. This methodology offers a more direct proxy for aggregate market intention, as it relies on costly transactions by users and investors, rather than inexpensive indirect signals from sources like Google searches or social media posts.

Building on our classification of on-chain transactions, we develop four hypotheses examining how token usage intensity and exchange-related activity influence token returns. The first two hypotheses explore the relationship between transaction volume and token valuation, distinguishing between peer-to-peer usage, which reflects functional engagement within a blockchain ecosystem, and exchange-related transactions, which may capture broader market demand and investor interest. The latter two hypotheses examine whether imbalances in transaction flows to and from exchanges—in both volume and count—convey aggregate market expectations and affect prices through supply-side or behavioral channels.

H1 (Peer-to-Peer Usage): An increase in peer-to-peer transactions (token "usage" transactions) is positively associated with token returns.

Tokens are designed to play essential roles within their ecosystems, such as facilitating payments, incentivizing participation, or enabling resource redistribution. Peer-to-peer transaction intensity—reflecting genuine usage within an ecosystem—should correlate positively with token prices. This hypothesis is rooted in network effects presented by Katz and Shapiro (1985, 1986, 1994), which suggest that as a token's user base expands, its utility and value also increases (Biais et al., 2019; Cong et al., 2021; Cong et al., 2022; Pagnotta, 2022; Sakkas and Urquhart, 2024; Prat et al., 2025).

H2 (Exchange-Related Transactions): An increase in exchange-related transactions (CeDex transactions) is positively associated with token returns.

While peer-to-peer transactions reflect usage within the ecosystem, exchange-related transactions can indicate heightened interest from broader market participants (Cong et al., 2021, 2022; Gandal and Halaburda, 2016; Halaburda et al., 2022; Li and Mann, 2025; Malinova and Park, 2023; Prat et al., 2025; Shams, 2020; Sockin and Xiong, 2023), suggesting an active demand in the secondary market, consistent with prior studies on investor demand (Barberis and Shleifer, 2003; Barberis et al., 2005).

H3 (Market Supply Pressure): An increase in the inflow volume of tokens deposited in exchanges, relative to the outflow volume of tokens withdrawn from exchanges, is negatively associated with token returns.

When the inflow of tokens to exchanges exceeds outflows, a higher volume of tokens becomes available for trading, potentially signaling increased sell-side liquidity. According to supply–demand dynamics, this net increase in available supply can create downward pressure on token prices, as the greater supply may outweigh current demand, consistent with findings of lockup expirations in IPO (Field and Hanka, 2021; Gibbs and Hao, 2018).

H4 (Aggregate Market Intention): An increase in the number of individual token deposit transactions to exchanges, relative to withdrawals, is negatively associated with token returns.

A higher ratio of incoming (deposit) transactions signals a greater intention to trade and potentially indicating bearish expectations; while a higher ratio of outgoing (withdrawal) transactions reflects a stronger intention to use/hold tokens and bullish expectations. This hypothesis explores whether shifts in aggregate intentions, as reflected in on-chain activity, influence token valuations, analogous to shifts in market sentiment (Rognone et al., 2020; Sapkota, 2022; Polyzos et al., 2024; Hadhri et al., 2025).

Taken together, these hypotheses explore both the functional and speculative dimensions of token usage, as well as how visible transaction flows may convey investor expectations and supply dynamics. By directly linking observable on-chain behaviors to token returns, we aim to provide empirical validation for the economic signals embedded in blockchain activity. In the following sections, we describe the data construction, variable definitions, and empirical strategy used to test these hypotheses.

3. Data

3.1. Data Description

The sample includes daily information on prices and transactions for all existing Ethereum blockchain-based projects with identifiable contract addresses listed on Coinmarketcap.com up to June 2021, totaling 512 projects. While the total number of tokens created on the Ethereum blockchain tops over 400,000, a minimum fraction relates to real projects, and of those, only a small percentage becomes listed at a cryptoasset exchange. Our dataset includes tokens designed for various use cases, such as governance (e.g., Augur – REP), data exchange (e.g., Ocean Protocol – OCEAN), cybersecurity (e.g., PolySwarm – NCT), and supply chain management (e.g., CargoX – CXO). This diversity allows us to analyze how different functional roles impact on-chain transaction behavior and price dynamics.

We obtain data on daily token blockchain transactions taking place between different wallets on the Ethereum blockchain from etherscan.io. For each token contract hash address (42-character string uniquely identifying a token creation address), we crawl information for all transactions involving the token, from each token's creation to June 10, 2021. This information includes the transaction address, sender address, receiver address (all of which are 66-character strings), transaction time (e.g, June-28–2021 05:36:08 PM + UTC), and quantity of tokens transferred in each transaction. This translates to over 180 million transactions. Following Foley et al., (2019), we manually identify all possible centralized and decentralized exchanges' wallet hash addresses,[9] reaching a total of 2,320 hash addresses, and identify transactions in which the receiver address or the sender address is a centralized or decentralized exchange. Secondary market daily prices and volume for all tokens are gathered from coinmarketcap.com, from the first available trading day until June 10, 2021.

3.2. Variables and Descriptive statistics

All variable definitions are presented in Table 1A. Descriptive statistics and correlation matrix are shown in Table 1B and Table 1C.

3.2.1. Proposed token usage measures

– Daily on-chain transactions: Daily number of on-chain transactions recorded in the Ethereum blockchain.

– Daily peer-to-peer transactions: Daily number of on-chain transactions recorded in the Ethereum blockchain and in which neither the receiver nor the sender is a Centralized or Decentralized Exchange address.

– Daily CeDex-related transactions: Daily number of on-chain transactions recorded in the Ethereum blockchain and in which the receiver or the sender is a Centralized or Decentralized Exchange address.

– Daily on-chain token volume: Daily number of tokens transferred in the Ethereum blockchain.

– Daily peer-to-peer token volume: Daily number of tokens transferred in the Ethereum blockchain and in which neither the receiver nor the sender is a Centralized or Decentralized Exchange address.

– Daily CeDex related volume: Daily number of tokens transferred in the Ethereum blockchain and in which the receiver or the sender is a Centralized or Decentralized Exchange address.

– Token Supply Pressure Ratio (TSPR): Value of the daily ratio of on-chain volume of supply and demand of tokens in the pool of tokens of exchanges (CeDex). The ratio is constructed as the daily proportion of total volume of tokens deposited in a CeDex address, over the total volume of tokens transferred, both "from" (withdrawn) or "to" (deposited) a CeDex address.

$$\mathrm{TSPR} = \frac{\sum \textit{Tokens deposited in CeDex}}{\sum \textit{Tokens withdrawn or deposited in CeDex}}$$

– Aggregate Intention Ratio (AIR): Proxy measuring daily aggregate intention. Users signal their intention to trade their tokens in the market by depositing their tokens from their individual on-chain wallet to a CeDex address. Users do not necessarily sell their tokens on the CeDex, but their tokens become available for trading. In contrast, users signal their potential intention to use/hold tokens by withdrawing tokens from a CeDex address to their individual on-chain wallet. The ratio is constructed as the daily ratio of inflow deposits to a CeDex addresses over the total number of CeDex-related transactions (both "from" (withdrawn) or "to" (deposited) a CeDex address).

[9] Examples of Centralized Exchanges we identify are Coinbase, Binance, Kraken, Gemini, GDAX, Huobi Global, Bithumb, Bitfinex, Bitstamp, Bittrex, KuCoin, FTX, Poloniex, bitFlyer, Celsius Network, BlockFi, youhodler, CEX.io, OKEx, Mercatox, and others. Examples of Decentralized Exchanges we identify are Uniswap (V2), Uphold, 0x Protocol, Venus, Tokenlon, Bisq, AirSwap, Blocknet, Barterdex, Sushiswap, Compound, BurgerSwap, Curve Finance, 1 in. Exchange, PancakeSwap, Paraswap, Stellar Decentralized Exchange, and others.

Table 1A
Variable definitions.

Variable	Definition
A. **Dependent Variable:**	
Daily token return	Daily return of the token. It is calculated as the daily closing price over the daily opening price of the token, minus 1. As there is no "closing price" in token markets, Coinmarketcap uses 00:00:00 + UTC as the reference time zone to construct the variables.
B. **Token usage variables:**	
Daily on-chain transactions	Daily number of on-chain transactions recorded in the Ethereum blockchain.
Daily peer-to-peer transactions	Daily number of on-chain transactions recorded in the Ethereum blockchain and in which neither the receiver nor the sender is a Centralized or Decentralized Exchange wallet.
Daily CeDex related transactions	Daily number of on-chain transactions recorded in the Ethereum blockchain and in which the receiver or the sender is a Centralized or Decentralized Exchange address
Daily on-chain token volume	Daily number of tokens transferred in the Ethereum blockchain.
Daily peer-to-peer token volume	Daily number of tokens transferred in the Ethereum blockchain and in which neither the receiver nor the sender is a Centralized or Decentralized Exchange wallet.
Daily CeDex related volume	Daily number of tokens transferred in the Ethereum blockchain and in which the receiver or the sender is a Centralized or Decentralized Exchange address.
Token Supply Pressure Ratio (TSPR)	Ratio that measures the daily ratio of on-chain volume of supply and demand of tokens in the pool of tokens of exchanges (CeDex). The ratio is constructed as the daily proportion of total volume of tokens deposited in a CeDex address, over the total volume of tokens transferred, both "from" (withdrawn) or "to" (deposited) a CeDex address.
Aggregate Intention Ratio (AIR):	Proxy measuring daily aggregate trading intention. Users signal their potential intention to trade their tokens in the market by moving their tokens from their on-chain wallet to a CeDex off-chain wallet. Investors do not necessarily sell their tokens on the CeDex, but the tokens become available for trading. The ratio is constructed as the daily ratio of inflow deposits to a CeDex addresses over the total number of CeDex-related transactions (both "from" (withdrawn) or "to" (deposited) a CeDex address).
C. **Control Variables:**	
Ether daily return	Daily returns on Ether, are considered as the industry reference on market returns. Previous papers such as Hu, Parlour, and Rajan (2018) show that individual cryptocurrency returns correlate with Bitcoin returns, and more specifically Ethereum blockchain based tokens correlate to Ether returns, considering it a more direct reference for controlling for the industry.
Volume	Total daily token trading volume measured in USD, in all exchanges (off-chain) that CoinMarketCap.com gathers information from (i.e. public exchanges that charge trading fees).
7-day volume	Mean volume of token trading in exchanges (off-chain) during the previous 7 days.
7-day return volatility	Volatility of token returns during the previous 7 days.
7-day Amihud illiquidity ratio	Proxy that measures illiquidity ratio of the token during the previous 7 days.

This table presents the definitions of the main variables used in the analysis.

Table 1B
Descriptive statistics.

Descriptive Statistics					
Variable	Obs	Mean	Std. Dev.	Min	Max
Daily return	246,974	0.015	0.60	−1	93.5
Previous daily return	246,453	0.015	0.60	−1	93.5
Ethereum returns	246,974	0	0.05	−0.42	0.34
Volume	246,974	942,424	5,659,613	0	6.98e + 08
Volume 7 day average	243,859	934,254	4,398,643	0	3.17e + 08
Amihud 7 day average	243,859	0.422	30.96	0	5,305
Return Volatility 7 day averagae	243,859	0.14	0.57	0	36
Daily peer-to-peer transactions	246,974	55.98	606.58	0	93,241
Daily CeDex related transactions	246,974	30.22	126.56	0	15,743
Daily on-chain volume	246,973	4.20e + 12	1.41e + 15	0	5.979e + 17
Daily peer-to-peer volume	246,973	667,583	74,524,659	0	2.113e + 10
Daily CeDex related volume	246,974	4.20e + 12	1.41e + 15	0	5.979e + 17
Ratio CeDex to transactions	206,144	0.45	0.30	0	1
Ratio CeDex to value	206,130	0.46	0.34	0	1

This table reports the descriptive statistics for the dependent variable (Daily token return) and selected independent variables.

$$\text{AIR} = \frac{\sum \textit{Number of inflow deposits in CeDex}}{\sum \textit{Number of inflow and outflow CeDex transactions}}$$

4. Estimation and results

We employ a two-step methodology to examine how our proposed measures of token-usage intensity correlate with abnormal token returns, accounting for both traditional market factors and token-specific factors.

Table 1C
Correlation Matrix.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Daily return	1.000													
(2) Previous daily return	−0.027	1.000												
(3) Ethereum returns	0.071	−0.005	1.000											
(4) Volume	0.013	0.009	0.010	1.000										
(5) Volume 7 day average	−0.006	−0.003	0.002	0.637	1.000									
(6) Amihud 7 day average	0.006	0.019	−0.001	−0.003	−0.004	1.000								
(7) Return Volatility 7 day average	0.049	0.426	−0.001	−0.004	−0.004	0.024	1.000							
(8) Daily peer-to-peer transactions	−0.001	−0.000	0.001	0.077	0.083	−0.002	−0.004	1.000						
(9) Daily CeDex related transactions	0.005	0.006	0.006	0.326	0.299	−0.004	−0.009	0.184	1.000					
(10) Daily on-chain volume	0.000	0.000	0.003	−0.000	−0.001	−0.000	0.000	0.001	0.001	1.000				
(11) Daily peer-to-peer volume	−0.001	0.001	−0.000	0.005	0.003	−0.000	0.001	0.009	0.035	−0.000	1.000			
(12) Daily CeDex related volume	0.000	0.000	0.003	−0.000	−0.001	−0.000	0.000	0.001	0.001	1.000	−0.000	1.000		
(13) Aggregate Intention Ratio (AIR)	−0.017	0.000	0.008	−0.018	−0.026	−0.001	−0.004	0.024	−0.011	−0.000	0.002	−0.000	1.000	
(14) Token Supply Pressure Ratio (TSPR)	−0.019	0.001	0.009	0.006	0.003	−0.001	−0.001	0.012	0.011	−0.003	0.005	−0.003	0.813	1.000

This table reports the pairwise correlation between selected variables.

4.1. Estimating abnormal token returns

In the first step, we estimate each token's abnormal return using a standard market model. Specifically, we calculate abnormal returns by regressing the token's return on the Bloomberg Galaxy Crypto Index (BGCI) return as the market return proxy, with the US 10-year government bond daily yield serving as the risk-free rate. This model allows us to capture the portion of each token's return that cannot be explained by general market movements, isolating token-specific residuals for further analysis.

The model for the first step is as follows:

$$R_{i,t} - Rf_t = \alpha_i + \beta_i(Rm_t - Rf_t) + \epsilon_{i,t} \tag{1}$$

where:

$R_{i,t}$ represents the return of token i at time t,
Rf_t is the daily risk-free rate, proxied by the US 10-year government bond yield at time t,
α_i is the intercept term for token i,
βi is the sensitivity of token's i return to the excess market return,
Rm_t is the market return, proxied by the return of the Bloomberg Galaxy Crypto Index (BGCI) at time t, and
$\epsilon_{i,t}$ represents the abnormal return or residual for token i at time t.

In the second step, we aim to determine whether token-specific factors, including our proposed on-chain measures, can explain these abnormal returns. We regress the residuals $\epsilon_{i,t}$ from the first step on a set of explanatory variables: our on-chain based metrics (token-related variables, Token Supply Pressure Ratio (TSPR), and Aggregate Intention Ratio (AIR), past returns, off-chain trading volume, and other token-specific control variables. This approach enables us to assess the explanatory power of token-specific behavior and market transaction intentions on residual returns while controlling for time-series effects and market conditions. The second step

Table 2
Token Usage Measures and Abnormal Token Returns.

Abnormal return	(1)	(2)	(3)	(4)	(5)	(6)
Ln Daily on-chain transactions	0.013***					
	(0.000)					
Ln Daily peer-to-peer transactions		0.010***				
		(0.000)				
Ln Daily CeDex related transactions			0.019***			
			(0.000)			
Ln Daily on-chain volume				0.017***		
				(0.002)		
Ln Daily peer-to-peer volume					0.010**	
					(0.033)	
Ln Daily CeDex related volume						0.018***
						(0.001)
Token FE Control	Yes	Yes	Yes	Yes	Yes	Yes
Previous day return	−0.091**	−0.091**	−0.091**	−0.091**	−0.091**	−0.091**
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Ether daily return	0.066***	0.066***	0.066***	0.066***	0.066***	0.066***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln Volume	0.134***	0.135***	0.132***	0.132***	0.135***	0.131***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.ln Volume 7 day	−0.163***	−0.163***	−0.163***	−0.164***	−0.163***	−0.163***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.ln Amihud 7 day	0.018	0.018	0.018	0.019	0.019	0.019
	(0.192)	(0.191)	(0.193)	(0.189)	(0.190)	(0.190)
L.ln RetVolatility 7 day	0.034**	0.034**	0.034**	0.034**	0.034**	0.034**
	(0.013)	(0.012)	(0.014)	(0.013)	(0.013)	(0.013)
N	220,698	220,698	220,698	220,697	220,697	220,698
R^2	0.017	0.017	0.017	0.017	0.017	0.017
adj. R^2	0.015	0.015	0.015	0.015	0.015	0.015
N_clusters	512	512	512	512	512	512

This table reports the standardized regression coefficients and the standard errors of regressions of abnormal token daily return on token usage measures (Total, peer-to-peer, and Cedex daily on-chain transactions, and Total, peer-to-peer, and CeDex daily on-chain volume), token characteristics (previous day return, volume, 7-day average volume, 7-day amihud illiquidity ratio, 7-day average return volatility) and token fixed effects. Abnormal returns were calculated as the residuals from a CAPM regression using Bloomberg's Galaxy Crypto Index (BGCI) as the market benchmark. These residuals capture the portion of token returns unexplained by overall crypto market movements. The sample includes all existing, successful, and listed Ethereum blockchain-based projects launched since the Ethereum blockchain inception and up to June 2021, listed on CoinMarketCap.com, with identifiable token contract addresses, totalling 512 projects. Each column represents a different regression. The standard errors are clustered at token level and are reported below the coefficients in parenthesis. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

model is formulated as follows:

$$\epsilon_{i,t} = \gamma_i + \gamma_1 ProposedMeasures_{i,t} + \gamma_2 ControlVariables_{i,t} + \nu_{i,t} \quad (2)$$

where:

$\epsilon_{i,t}$ is the abnormal excess return estimated in equitation 1,
γ_i is the intercept term for token *i*,
γ_1 is the sensitivity of token's *i* abnormal return to each proposed measure of on-chain behaviour,
Proposed Measures $_{i,t}$ are the different measures of on-chain behaviour (Token-related Variables, Token Supply Pressure Ratio (TSPR), and Aggregate Intention Ratio (AIR) described in section 4.2.2 and 4.2.3, for token *i* at time *t*,
γ_2 is a vector representing the sensitivity of tokens' abnormal return to each token's control variables,
Control Variables$_{i,t}$ is a matrix of the control variables described in section 4.2.4 for token *i* at time *t*,
$\nu_{i,t}$ represents the estimation residual for token *i* at time *t*.

This two-step approach allows us to isolate the contribution of on-chain transaction data, disentangling speculative activity from functional token usage. By doing so, we gain insights into how these on-chain factors impact token prices beyond general market influences, providing a deeper understanding of their role in explaining token returns.

In Tables 2 through 5, we test whether the different measures of token usage, token supply pressure ratio (TSPR), and aggregate intention ratio (AIR) are correlated with abnormal token returns. Each column represents a regression on the abnormal return of each token, obtained using a market model using the Bloomberg's Galaxy Crypto Index (BGCI) return as market return and the US 10 years government bond daily yield as the risk-free rate. As presented in equation (2), in all regressions we control for previous-day token returns, ETH returns, traded volume, average previous 7-day volume, average previous 7-day Amihud illiquidity ratio and average previous 7-day return volatility. We include token fixed effects and clustering of standard errors at token level.

4.2. Main results

Table 2 reports the estimation results testing whether different forms of token usage intensity are positively associated with abnormal token returns, as proposed in Hypotheses 1 and 2. Columns (1) through (3) present results based on the number of on-chain transactions, while Columns (4) through (6) use the total volume of tokens transferred. Across all specifications, we find a positive and

Table 3
Token Supply Pressure Ratio and Abnormal Token Returns.

Abnormal return	(1)	(2)	(3)	(4)
Token Supply Pressure Ratio (TSPR)	−0.021***	−0.021***	−0.021***	−0.021***
	(0.000)	(0.000)	(0.000)	(0.000)
LnDaily CeDex related volume		0.022***		0.022***
		(0.001)		(0.001)
Ratio off/on-chain Volume			−0.001***	−0.000
			(0.001)	(0.535)
Token FE Control	Yes	Yes	Yes	Yes
Previous day return	−0.078**	−0.078**	−0.078**	−0.078**
	(0.018)	(0.018)	(0.018)	(0.018)
Ether daily return	0.068***	0.068***	0.068***	0.068***
	(0.000)	(0.000)	(0.000)	(0.000)
lnVolume	0.146***	0.137***	0.146***	0.137***
	(0.000)	(0.000)	(0.000)	(0.000)
L.lnVolume 7 day	−0.176***	−0.180***	−0.176***	−0.180***
	(0.000)	(0.000)	(0.000)	(0.000)
L.Amihud 7 day	0.005	0.005	0.005	0.005
	(0.193)	(0.201)	(0.193)	(0.201)
L.RetVolatility 7 day	0.021**	0.021**	0.021**	0.021**
	(0.028)	(0.030)	(0.028)	(0.030)
N	190,340	19,0340	190,339	190,339
R^2	0.017	0.017	0.017	0.017
adj. R^2	0.014	0.014	0.014	0.014
N_clust	498	498	498	498

This table reports the standardized regression coefficients and the standard errors of regressions of abnormal token daily return on Token Supply Pressure Ratio (TPSR), token characteristics (previous day return, volume, 7-day average volume, 7-day Amihud illiquidity ratio, 7-day average return volatility) and token fixed effects. Abnormal returns were calculated as the residuals from a CAPM regression using Bloomberg's Galaxy Crypto Index (BGCI) as the market benchmark. These residuals capture the portion of token returns unexplained by overall crypto market movements. The sample includes all existing, successful, and listed Ethereum blockchain-based projects launched since the Ethereum blockchain inception and up to June 2021, listed on CoinMarketCap.com, with identifiable token contract addresses, totalling 498 projects. Each column represents a different regression. The standard errors are clustered at token level and are reported below the coefficients in parenthesis. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Table 4
Aggregate Intention Ratio and Abnormal Token Returns.

Abnormal return	(1)	(2)	(3)	(4)
Aggregate Intention Ratio (AIR)	−0.019***	−0.020***	−0.019***	−0.020***
	(0.000)	(0.000)	(0.000)	(0.000)
LnDaily CeDex related transactions		0.020***		0.020***
		(0.000)		(0.000)
Ratio off/on-chain Volume			−0.001***	−0.001***
			(0.000)	(0.006)
Token FE Control	Yes	Yes	Yes	Yes
Previous day return	−0.077**	−0.077**	−0.077**	−0.077**
	(0.018)	(0.018)	(0.018)	(0.018)
Ether daily return	0.068***	0.068***	0.068***	0.068***
	(0.000)	(0.000)	(0.000)	(0.000)
lnVolume	0.149***	0.142***	0.149***	0.142***
	(0.000)	(0.000)	(0.000)	(0.000)
L.lnVolume 7 day	−0.175***	−0.178***	−0.175***	−0.178***
	(0.000)	(0.000)	(0.000)	(0.000)
L.lnAmihud 7 day	0.023	0.023	0.023	0.023
	(0.244)	(0.248)	(0.244)	(0.248)
L.lnRetVolatility 7 day	0.027***	0.026**	0.027***	0.026**
	(0.007)	(0.010)	(0.007)	(0.010)
N	190,343	190,343	190,342	190,342
R^2	0.017	0.017	0.017	0.017
adj. R^2	0.015	0.015	0.015	0.015
N_clust	498	498	498	498

This table reports the standardized regression coefficients and the standard errors of regressions of abnormal token daily return on Aggregate Intention Ratio (AIR), token characteristics (previous day return, volume, 7-day average volume, 7-day Amihud illiquidity ratio, 7-day average return volatility) and token fixed effects. Abnormal returns were calculated as the residuals from a CAPM regression using Bloomberg's Galaxy Crypto Index (BGCI) as the market benchmark. These residuals capture the portion of token returns unexplained by overall crypto market movements. The sample includes all existing, successful, and listed Ethereum blockchain-based projects launched since the Ethereum blockchain inception and up to June 2021, listed on CoinMarketCap.com, with identifiable token contract addresses, totalling 498 projects. Each column represents a different regression. The standard errors are clustered at token level and are reported below the coefficients in parenthesis. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

statistically significant association between on-chain activity and returns, providing robust support for both hypotheses.

In particular, Columns (2) and (4), which isolate peer-to-peer transactions, confirm Hypothesis1, which posits that increased functional usage of tokens within their ecosystems leads to higher market valuations. This finding reinforces the network effect mechanisms theorized by Katz and Shapiro (1985, 1986, 1994) and aligns with recent theoretical models emphasizing the role of genuine token utility in supporting long-term value (Cong et al., 2021, 2022; Prat et al., 2025). As tokens become more embedded in real economic interactions by facilitating payments, resource allocation, or governance, their utility expands alongside the user base, leading to positive price responses. Our evidence thus supports the view that token valuation increasingly resembles fundamental-based pricing during the "mature adoption" phase theorized in lifecycle models (Mayer, 2022; Prat et al., 2025).

Columns (3) and (6) instead focus on exchange-related (CeDex) transactions, which reflect speculative or trading-driven activity. The positive coefficients in these columns support Hypothesis 2, indicating that market-facing activity also drives token prices upward. This result connects to prior work on informational trading and investor attention (Barberis and Shleifer, 2003; Shams, 2020), and highlights that the signaling function of secondary-market activity, particularly as captured on-chain, can be capitalized into token values. The result also aligns with theoretical models where trading activity reveals or even generates value through increased visibility, liquidity, and perceived demand (Sockin and Xiong, 2023).

Together, these findings suggest that both functional engagement and market speculation are priced into token values, each through distinct yet complementary channels. They demonstrate that on-chain transaction data offer valuable proxies to differentiate usage-driven value from investor-driven demand, addressing long-standing calls in the literature for more granular measures of cryptocurrency fundamentals (Foley et al., 2019; Benedetti and Nikbakht, 2021). Control variables across all specifications behave as expected and are consistent with prior literature, adding robustness to the interpretation of our usage-related coefficients.

Table 3 examines Hypothesis 3, which posits that a net inflow of tokens to centralized or decentralized exchanges (CeDex) increases sell-side liquidity and exerts downward pressure on token prices. We proxy this mechanism using the Token Supply Pressure Ratio (TSPR). Column (1) serves as the baseline, including only TSPR and controls. Columns (2) and (3) successively introduce CeDex-specific activity metrics such as on-chain trading volume and the off-chain/on-chain CeDex volume ratio. Column (4) includes the full set of controls. Across Columns (1) to (4), the coefficient on TSPR remains consistently negative and statistically significant, supporting the hypothesis that a relative increase in deposit volume, interpreted as a measure of latent supply pressure, has a detrimental effect on token returns. As with Table 2, all control variables show signs and magnitudes consistent with prior studies.

These findings align with standard supply–demand mechanisms in financial markets and extend empirical insights from prior work on IPO lock-up expirations (Field and Hanka, 2001; Gibbs and Hao, 2018), where sudden increases in tradable supply depress valuations. In the context of token markets, our results show that on-chain flow imbalances serve as a transparent and timely signal of

Table 5
Token Supply Pressure Ratio, Aggregate Intention Ratio, and Abnormal Token Returns.

Abnormal return	(1)	(2)	(3)	(4)
Aggregate Intention Ratio (AIR)	−0.007**	−0.007**	−0.007**	−0.007**
	(0.038)	(0.043)	(0.039)	(0.043)
Token Supply Pressure Ratio (TSPR)	−0.015***	−0.016***	−0.015***	−0.016***
	(0.000)	(0.000)	(0.000)	(0.000)
LnDaily CeDex related transactions		0.015**		0.015**
		(0.046)		(0.046)
Ln_Daily CeDex related volume		0.012		0.011
		(0.247)		(0.249)
Ratio off/on-chain Volume			−0.001***	−0.000
			(0.001)	(0.330)
Token FE Control	Yes	Yes	Yes	Yes
Previous day return	−0.078**	−0.078**	−0.078**	−0.078**
	(0.018)	(0.018)	(0.018)	(0.018)
Ether daily return	0.068***	0.068***	0.068***	0.068***
	(0.000)	(0.000)	(0.000)	(0.000)
lnVolume	0.146***	0.136***	0.146***	0.136***
	(0.000)	(0.000)	(0.000)	(0.000)
L.lnVolume 7 day	−0.176***	−0.180***	−0.176***	−0.180***
	(0.000)	(0.000)	(0.000)	(0.000)
L.Amihud 7 day	0.005	0.005	0.005	0.005
	(0.194)	(0.207)	(0.194)	(0.207)
L.RetVolatility 7 day	0.021**	0.021**	0.021**	0.021**
	(0.028)	(0.031)	(0.028)	(0.031)
N	190,340	190,340	190,339	190,339
R^2	0.017	0.017	0.017	0.017
adj. R^2	0.014	0.014	0.014	0.014
N_clust	498	498	498	498

This table reports the standardized regression coefficients and the standard errors of regressions of abnormal token daily return on Token Supply Pressure Ratio (TSPR), Aggregate Intention Ratio (AIR), token characteristics (previous day return, volume, 7-day average volume, 7-day Amihud illiquidity ratio, 7-day average return volatility) and token fixed effects. Abnormal returns were calculated as the residuals from a CAPM regression using Bloomberg's Galaxy Crypto Index (BGCI) as the market benchmark. These residuals capture the portion of token returns unexplained by overall crypto market movements. The sample includes all existing, successful, and listed Ethereum blockchain-based projects launched since the Ethereum blockchain inception and up to June 2021, listed on CoinMarketCap.com, with identifiable token contract addresses, totalling 498 projects. Each column represents a different regression. The standard errors are clustered at token level and are reported below the coefficients in parenthesis. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

excess supply, made observable through blockchain data.

Table 4 evaluates Hypothesis 4, which theorizes that a higher Aggregate Intention Ratio (AIR) suggests a greater share of addresses preparing to sell, potentially reflecting bearish expectations or lower token adoption. Across all columns, AIR shows a negative and significant relationship with token returns, supporting the hypothesis that observable trading intentions, as expressed through transaction counts rather than volumes, carry predictive value. As with Table 3, the four specifications incrementally introduce controls related to transaction activity and off-chain market influence, yet the AIR coefficient remains stable and significant throughout. This result builds on the idea that transaction-level data offer a more direct proxy for sentiment than passive measures such as search trends, social media attention, or music listening behavior (Rognone et al., 2020; Sapkota, 2022; Polyzos et al., 2024; Hadhri et al., 2025). By focusing on the number of transactions, each incurring in transaction fees, the AIR provides a behavior-based intention measure.

Finally, Table 5 jointly tests Hypotheses 3 and 4, incorporating both TSPR and AIR in the same regression framework to evaluate their combined explanatory power. The results indicate that both metrics independently and significantly explain token returns, even when controlling for CeDex transaction intensity, trading volume, and the off-chain/on-chain market ratio. This joint estimation confirms that volume-based supply dynamics and count-based trading intentions provide distinct and complementary information about price pressure and market sentiment in token ecosystems.

Overall, the results presented in Tables 2 through 5 provide strong empirical support for our hypotheses, highlighting the significant role of token usage intensity, exchange flow imbalances, and aggregate transaction intention in explaining abnormal token returns. The positive correlation between on-chain transaction metrics and token prices confirms the importance of functional token usage, while the observed negative impact of token supply pressure ratio and aggregate intention ratio emphasize the sensitivity of token prices to investor behaviour within crypto-exchange environments. These findings contribute to a deeper understanding of how on-chain transactional data reflects underlying demand, supply dynamics, and aggregate transaction intentions, reinforcing the value of on-chain analysis as a direct and reliable measure of economic signals in token markets.

4.3. Robustness check

To validate the reliability of our empirical findings, we conduct several robustness checks addressing potential concerns related to model specification and dynamic effects.

4.3.1. Alternative market Benchmarks

We first assess whether our results are sensitive to the choice of market return proxy in the first-stage abnormal return estimation. While the baseline specification employs the Bloomberg Galaxy Crypto Index (BGCI) as the market benchmark, we re-estimate the full set of regressions using the Crypto Market Returns Index developed by Polyzos and Youssef (2025). This index offers broader asset coverage and a theoretically grounded representation of the cryptocurrency market, extending beyond the large-cap composition of the BGCI. By incorporating a wider range of assets and weighting schemes designed to capture the underlying structure of the crypto ecosystem, this index mitigates potential biases from relying on a single, possibly narrow, market proxy. Testing our hypotheses against this benchmark therefore serves as a stronger verification that our findings are not an artifact of the BGCI's composition.

Table 6 reports the robustness results for Hypotheses 1 and 2, which test whether peer-to-peer and exchange-related transaction intensity are positively associated with abnormal token returns. The findings remain consistent with our baseline: both forms of on-chain transaction activity display positive and statistically significant coefficients across specifications. This persistence confirms that functional usage and speculative market-facing activity each contribute to token valuations, independent of the chosen market proxy, reinforcing the view that network effects and investor attention dynamics are structural drivers of token prices.

Table 7 presents the results for Hypothesis 3, which posits that net inflows of tokens to exchanges, proxied by the Token Supply Pressure Ratio (TSPR) exert downward pressure on prices. Under the alternative benchmark, TSPR retains its negative and statistically significant association with abnormal returns. This robustness underscores that supply-side imbalances have an adverse price impact regardless of whether market performance is measured by BGCI or the broader Polyzos and Youssef (2025) index, aligning with supply–demand dynamics observed in other financial markets.

Table 8 examines Hypothesis 4, which tests whether a higher Aggregate Intention Ratio (AIR), the proportion of deposit transactions relative to total CeDex transactions, signals bearish market expectations and correlates negatively with returns. Results again mirror the baseline model: AIR maintains a negative and significant coefficient across specifications, reinforcing its role as a more

Table 6

Token Usage Measures and Abnormal Token Returns Using Alternative Crypto Market Returns Benchmark.

Abnormal return	(1)	(2)	(3)	(4)	(5)	(6)
Ln Daily on-chain transactions	0.014***					
	(0.000)					
Ln Daily peer-to-peer transactions		0.010***				
		(0.000)				
Ln Daily CeDex related transactions			0.019***			
			(0.000)			
Ln Daily on-chain volume				0.016***		
				(0.002)		
Ln Daily peer-to-peer volume					0.010**	
					(0.031)	
Ln Daily CeDex related volume						0.018***
						(0.001)
Token FE Control	Yes	Yes	Yes	Yes	Yes	Yes
Previous day return	−0.074***	−0.074***	−0.074***	−0.074***	−0.074***	−0.074***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)
Ether daily return	0.067***	0.067***	0.067***	0.067***	0.067***	0.067***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln Volume	0.133***	0.135***	0.131***	0.131***	0.134***	0.131***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.ln Volume 7 day	−0.163***	−0.163***	−0.163***	−0.164***	−0.163***	−0.163***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.ln Amihud 7 day	0.018	0.018	0.018	0.018	0.018	0.018
	(0.195)	(0.194)	(0.196)	(0.192)	(0.193)	(0.193)
L.ln RetVolatility 7 day	0.033**	0.033**	0.033**	0.033**	0.033**	0.033**
	(0.012)	(0.011)	(0.013)	(0.012)	(0.012)	(0.012)
N	221,031	221,031	221,031	221,030	221,030	221,031
R^2	0.015	0.015	0.015	0.015	0.015	0.015
adj. R^2	0.013	0.013	0.013	0.013	0.013	0.013
N_clusters	512	512	512	512	512	512

This table reports the standardized regression coefficients and the standard errors of regressions of abnormal token daily return on token usage measures (Total, peer-to-peer, and Cedex daily on-chain transactions, and Total, peer-to-peer, and CeDex daily on-chain volume), token characteristics (previous day return, volume, 7-day average volume, 7-day Amihud illiquidity ratio, 7-day average return volatility) and token fixed effects. Abnormal returns were calculated as the residuals from a CAPM regression using the Crypto Market Returns Index from Polyzos & Youssef (2025) as the market benchmark. These residuals capture the portion of token returns unexplained by broad crypto market movements. The sample includes all existing, successful, and listed Ethereum blockchain-based projects launched since the Ethereum blockchain inception and up to June 2021, listed on CoinMarketCap.com, with identifiable token contract addresses, totaling 512 projects. Each column represents a different regression. The standard errors are clustered at token level and are reported below the coefficients in parenthesis. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Table 7
Token Supply Pressure Ratio and Abnormal Token Returns Using Alternative Crypto Market Returns Benchmark.

Abnormal return	(1)	(2)	(3)	(4)
Token Supply Pressure Ratio (TSPR)	−0.019***	−0.020***	−0.019***	−0.020***
	(0.000)	(0.000)	(0.000)	(0.000)
LnDaily CeDex related transactions		0.021***		0.021***
		(0.000)		(0.000)
Ratio off/on-chain Volume			−0.001***	−0.001**
			(0.002)	(0.015)
Token FE Control	Yes	Yes	Yes	Yes
Previous day return	−0.059***	−0.059***	−0.059***	−0.059***
	(0.001)	(0.001)	(0.001)	(0.001)
Ether daily return	0.070***	0.070***	0.070***	0.070***
	(0.000)	(0.000)	(0.000)	(0.000)
lnVolume	0.148***	0.141***	0.148***	0.141***
	(0.000)	(0.000)	(0.000)	(0.000)
L.lnVolume 7 day	−0.175***	−0.177***	−0.175***	−0.177***
	(0.000)	(0.000)	(0.000)	(0.000)
L.lnAmihud 7 day	0.023	0.022	0.023	0.022
	(0.239)	(0.244)	(0.239)	(0.244)
L.lnRetVolatility 7 day	0.024***	0.023***	0.024***	0.023***
	(0.003)	(0.005)	(0.003)	(0.005)
N	190,676	190,676	190,675	190,675
R^2	0.015	0.015	0.015	0.015
adj. R^2	0.013	0.013	0.013	0.013
N_clusters	498	498	498	498

This table reports the standardized regression coefficients and the standard errors of regressions of abnormal token daily return on Token Supply Pressure Ratio (TPSR), token characteristics (previous day return, volume, 7-day average volume, 7-day Amihud illiquidity ratio, 7-day average return volatility) and token fixed effects. Abnormal returns were calculated as the residuals from a CAPM regression using the Crypto Market Returns Index from Polyzos & Youssef (2025) as the market benchmark. These residuals capture the portion of token returns unexplained by broad crypto market movements. The sample includes all existing, successful, and listed Ethereum blockchain-based projects launched since the Ethereum blockchain inception and up to June 2021, listed on CoinMarketCap.com, with identifiable token contract addresses, totalling 498 projects. Each column represents a different regression. The standard errors are clustered at token level and are reported below the coefficients in parenthesis. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

direct, behavior-based proxy for market sentiment.

Table 9 jointly tests Hypotheses 3 and 4 by including both TSPR and AIR in the same specification to assess their combined explanatory power. Both metrics remain significant and retain their expected signs. This confirms that volume-based supply pressures and count-based trading intentions provide distinct and complementary information about price formation in token markets. The robustness of these joint effects across market proxies further strengthens our argument that on-chain transactional measures capture fundamental structural drivers of token returns.

Taken together, the evidence from Tables 6–9 confirms that the relationships documented in our baseline analysis are not contingent on the choice of market index. Using the Polyzos and Youssef (2025) benchmark yields results consistent in sign, magnitude, and statistical significance with those obtained using BGCI, reinforcing the theoretical claim that network effects, supply imbalances, and aggregate trading intentions are stable features of token market dynamics.

As a complementary robustness check, we also re-estimate the models using Ethereum excess returns as the market benchmark, reflecting Ethereum's role as the foundational layer for all tokens in our sample. These results, reported in the Online Appendix Tables A.1 to A.4 are consistent with both the BGCI and Polyzos and Youssef (2025) index-based estimations, further confirming that our conclusions are not contingent on the choice of market return proxy.

4.3.2. Lagged variables and dynamic effects.

Lastly, we explore the potential for dynamic relationships by incorporating one-period lags of both the dependent variable (abnormal returns) and key explanatory variables. This test captures delayed effects in market response and helps address concerns about autocorrelation or reverse causality. The main coefficients remain stable and significant across these models, reinforcing the interpretation that the observed relationships reflect contemporaneous and persistent pricing effects stemming from on-chain transactional behavior (see Online Appendix Tables A.5 to A.8).

5. Conclusion

This study contributes to the growing body of literature on crypto-asset markets by introducing novel proxies for measuring real token usage intensity, CeDex token flow imbalance and aggregate intentions, and analysing their impact on token returns. By distinguishing between token use transactions and trading −related transactions, our approach offers fresh insights into how user behaviour influences token valuations. This separation allows us to empirically examine token usage within its ecosystem, shifting the focus from token adoption as a network effect to the actual functional use of tokens—a perspective previously unexplored in crypto-

Table 8
Aggregate Intention Ratio and Abnormal Token Returns Using Alternative Crypto Market Returns Benchmark.

Abnormal return	(1)	(2)	(3)	(4)
Aggregate Intention Ratio (AIR)	−0.020***	−0.020***	−0.020***	−0.020***
	(0.000)	(0.000)	(0.000)	(0.000)
LnDaily CeDex related transactions		0.022***		0.022***
		(0.000)		(0.000)
Ratio off/on-chain Volume			−0.001***	−0.000
			(0.003)	(0.623)
Token FE Control	Yes	Yes	Yes	Yes
Previous day return	−0.060***	−0.060***	−0.060***	−0.060***
	(0.002)	(0.002)	(0.002)	(0.002)
Ether daily return	0.070***	0.070***	0.070***	0.070***
	(0.000)	(0.000)	(0.000)	(0.000)
lnVolume	0.145***	0.137***	0.145***	0.137***
	(0.000)	(0.000)	(0.000)	(0.000)
L.lnVolume 7 day	−0.176***	−0.179***	−0.176***	−0.179***
	(0.000)	(0.000)	(0.000)	(0.000)
L.lnAmihud 7 day	0.005	0.005	0.005	0.005
	(0.185)	(0.193)	(0.185)	(0.193)
L.lnRetVolatility 7 day	0.019**	0.019**	0.019**	0.019**
	(0.034)	(0.038)	(0.034)	(0.038)
N	190,673	190,673	190,672	190,672
R^2	0.015	0.015	0.015	0.015
adj. R^2	0.012	0.012	0.012	0.012
N_clusters	498	498	498	498

This table reports the standardized regression coefficients and the standard errors of regressions of abnormal token daily return on Aggregate Intention Ratio (AIR), token characteristics (previous day return, volume, 7-day average volume, 7-day Amihud illiquidity ratio, 7-day average return volatility) and token fixed effects. Abnormal returns were calculated as the residuals from a CAPM regression using the Crypto Market Returns Index from Polyzos & Youssef (2025) as the market benchmark. These residuals capture the portion of token returns unexplained by broad crypto market movements. The sample includes all existing, successful, and listed Ethereum blockchain-based projects launched since the Ethereum blockchain inception and up to June 2021, listed on CoinMarketCap.com, with identifiable token contract addresses, totalling 498 projects. Each column represents a different regression. The standard errors are clustered at token level and are reported below the coefficients in parenthesis. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

asset research.

Our findings indicate that both token usage intensity and exchange-related transactions are correlated with token returns. This suggests that investors are concerned with the adoption, usage and network dynamics of tokens, as well as supply imbalances and aggregate transaction intention measures inferred from transaction activities involving CeDexs.

These results offer important implications for investors and market participants. For investors, the findings underscore the relevance of monitoring exchange activity, as it appears to capture supply–demand imbalances and shift in aggregate intentions, which affect token pricing. Additionally, our analysis suggests that on-chain transaction data can serve as a reliable economic signal in assessing market conditions, providing a more direct indicator of users' intentions than traditional measures related to market sentiment such search engine queries or social media activity. For market regulators, the results emphasize the need to understand how on-chain data reflects underlying market dynamics, offering potential tools for monitoring liquidity and aggregate intentions in token markets.

A key limitation of our study is that our dataset ends in 2021. While this period already encompasses more than 180 million Ethereum-based token transactions, it does not capture the most recent structural developments in the digital token ecosystem, such as the increased participation of institutional investors. However, we do not expect these shifts to fundamentally alter the core behavioral patterns we document; if anything, they may reinforce the tendency of investors to observe and follow the actions of others. Future research could build on our findings by incorporating more recent data and explicitly examining how different types of market participants—retail versus institutional—contribute to these dynamics. Expanding the analysis to other blockchain ecosystems and cryptoasset types could further illuminate the unique drivers of value in different segments of the crypto market. Additionally, future studies could explore the relationship between other forms of on-chain activity, such as staking and governance participation, potentially offering a more comprehensive perspective on the diverse functions of blockchain assets. Finally, our methodology of using on-chain transactional data as a market liquidity and aggregate intention measure could serve as a foundation for the development of new tools and metrics that enhance market transparency and investor decision-making in the rapidly evolving field of token markets.

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Table 9
Token Supply Pressure Ratio, Aggregate Intention Ratio, and Abnormal Token Returns Using Alternative Crypto Market Returns Benchmark.

Abnormal return	(1)	(2)	(3)	(4)
Aggregate Intention Ratio (AIR)	−0.007**	−0.007**	−0.007**	−0.007**
	(0.038)	(0.042)	(0.038)	(0.042)
Token Supply Pressure Ratio (TSPR)	−0.015***	−0.016***	−0.015***	−0.016***
	(0.000)	(0.000)	(0.000)	(0.000)
LnDaily CeDex related transactions		0.016**		0.016**
		(0.042)		(0.043)
Ln_Daily CeDex related volume		0.011		0.011
		(0.249)		(0.251)
Ratio off/on-chain Volume			−0.001***	−0.000
			(0.004)	(0.388)
Token FE Control	Yes	Yes	Yes	Yes
Previous day return	−0.060***	−0.060***	−0.060***	−0.060***
	(0.002)	(0.002)	(0.002)	(0.002)
Ether daily return	0.070***	0.070***	0.070***	0.070***
	(0.000)	(0.000)	(0.000)	(0.000)
lnVolume	0.145***	0.135***	0.145***	0.135***
	(0.000)	(0.000)	(0.000)	(0.000)
L.lnVolume 7 day	−0.176***	−0.180***	−0.176***	−0.180***
	(0.000)	(0.000)	(0.000)	(0.000)
L.Amihud 7 day	0.005	0.005	0.005	0.005
	(0.186)	(0.199)	(0.186)	(0.199)
L.RetVolatility 7 day	0.019**	0.019**	0.019**	0.019**
	(0.035)	(0.039)	(0.035)	(0.039)
N	190,673	190,673	190,672	190,672
R^2	0.015	0.015	0.015	0.015
adj. R^2	0.012	0.012	0.012	0.012
N_clusters	498	498	498	498

This table reports the standardized regression coefficients and the standard errors of regressions of abnormal token daily return on Token Supply Pressure Ratio (TSPR), Aggregate Intention Ratio (AIR), token characteristics (previous day return, volume, 7-day average volume, 7-day Amihud illiquidity ratio, 7-day average return volatility) and token fixed effects. Abnormal returns were calculated as the residuals from a CAPM regression using the Crypto Market Returns Index from Polyzos & Youssef (2025) as the market benchmark. These residuals capture the portion of token returns unexplained by broad crypto market movements. The sample includes all existing, successful, and listed Ethereum blockchain-based projects launched since the Ethereum blockchain inception and up to June 2021, listed on CoinMarketCap.com, with identifiable token contract addresses, totalling 498 projects. Each column represents a different regression. The standard errors are clustered at token level and are reported below the coefficients in parenthesis. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

CRediT authorship contribution statement

Hugo Benedetti: Writing – review & editing, Writing – original draft, Supervision, Methodology. **Gabriel Rodriguez-Garnica:** Writing – original draft, Validation, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

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References

Abadi, J., Brunnermeier, M., 2018. Blockchain economics. *National Bureau of*. Econ. Res. w25407.
Adhami, S., Giudici, G., Martinazzi, S., 2018. Why do businesses go crypto? An empirical analysis of initial coin offerings. J. Econ. Bus. 100. C , 64–75.
Athey, S., Parashkevov, I., Sarukkai, V., Xia, J., 2016. Bitcoin pricing, adoption, and usage: theory and evidence. Stanford University Graduate School of Business Research Paper No. 16–42.
Barberis, N., Shleifer, A., 2003. Style investing. J. Financ. Econ. 68 (2), 161–199.
Barberis, N., Shleifer, A., Wurgler, J., 2005. Comovement. J. Financ. Econ. 75 (2), 283–317.
Benedetti, H., Kostovetsky, L., 2021. Digital tulips? returns to investors in initial coin offerings. Finance 66, 101786.
Benedetti, H., Nikbakht, E., 2021. Returns and network growth of digital tokens after cross-listings. Finance 66, 101853.

Benedetti, H., Caceres, C., Abarzúa, L.Á., 2023. Utility tokens. In: The Emerald Handbook on Cryptoassets: Investment Opportunities and Challenges. Emerald Publishing Limited, pp. 79–92.
Biais, B., Bisiere, C., Bouvard, M., Casamatta, C., 2019. The blockchain folk theorem. Rev. Financ. Stud. 32 (5), 1662–1715.
Bleher, J., Dimpfl, T., 2019. Today I got a million, tomorrow, I don't know: on the predictability of cryptocurrencies by means of Google search volume. Int. Rev. Financ. Anal. 63, 147–159.
Bonaparte, Y., 2022. Time horizon and cryptocurrency ownership: is crypto not speculative? J. Int. Financ. Mark. Inst. Money 79, 101609.
Cheah, E.T., Fry, J., 2015. Speculative bubbles in Bitcoin markets? an empirical investigation into the fundamental value of Bitcoin. Econ. Lett. 130, 32–36.
Chen, Y., Zhang, L., Bouri, E., 2024. Co-Bubble transmission across clean and dirty cryptocurrencies: Network and portfolio analysis. J. Int. Money Financ. 145, 103108.
Ciner, C., Lucey, B., Yarovaya, L., 2022. Determinants of cryptocurrency returns: a Lasso quantile regression approach. Financ. Res. Lett. 49, 102990.
Cong, L.W., Li, Y., Wang, N., 2021. Tokenomics: Dynamic adoption and valuation. Rev. Financ. Stud. 34 (3), 1105–1155.
Cong, L.W., Li, Y., Wang, N., 2022. Token-based platform finance. J. Financ. Econ. 144 (3), 972–991.
Corbet, S., Larkin, C., Lucey, B., Yarovaya, L., 2018. Datestamping the Bitcoin and Ethereum bubbles. Financ. Res. Lett. 26, 81–88.
Corbet, S., Lucey, B., Urquhart, A., Yarovaya, L., 2019. Cryptocurrencies as a financial asset: a systematic analysis. Int. Rev. Financ. Anal. 62, 182–199.
Dai, P.F., Goodell, J.W., Huynh, L.D.T., Liu, Z., Corbet, S., 2023. Understanding the transmission of crash risk between cryptocurrency and equity markets. Financ. Rev. 58 (3), 539–573.
Dhawan, A., Putniņš, T.J., 2023. A new wolf in town? Pump-and-dump manipulation in cryptocurrency markets. Eur. Finan. Rev. 27 (3), 935–975.
Duan, K., Zhang, L., Urquhart, A., Yao, K., Peng, L., 2024. Do clean and dirty cryptocurrencies connect financial assets differently? the perspective of market inefficiency. Res. Int. Bus. Financ. 70, 102351.
Field, L.C., Hanka, G., 2001. The expiration of IPO share lockups. J. Financ. 56 (2), 471–500.
Foley, S., Karlsen, J.R., Putniņš, T.J., 2019. Sex, drugs, and bitcoin: how much illegal activity is financed through cryptocurrencies? Rev. Financ. Stud. 32 (5), 1798–1853.
Gandal, N., Halaburda, H., 2016. Can we predict the winner in a market with network effects? Competition in Cryptocurrency Market. Games 7 (3), 16.
Gibbs, M., Hao, Q., 2018. Short selling around the expiration of IPO share lockups. J. Bank. Financ. 88, 30–43.
Goldstein, I., Gupta, D., Sverchkov, R., 2024. Utility tokens as a commitment to competition. J. Financ. 79 (6), 4197–4232.
Griffin, J.M., Shams, A., 2020. Is Bitcoin really untethered? J. Financ. 75 (4), 1913–1964.
Grobys, K., Junttila, J., 2021. Speculation and lottery-like demand in cryptocurrency markets. J. Int. Financ. Mark. Inst. Money 71, 101289.
Guégan, D., Renault, T., 2021. Does investor sentiment on social media provide robust information for Bitcoin returns predictability? Financ. Res. Lett. 38, 101494.
Hadhri, S., Younus, M., Naeem, M.A., Yarovaya, L., 2025. Listening to the Market: Music sentiment and cryptocurrency returns. J. Int. Money Financ. 103394.
Halaburda, H., Haeringer, G., Gans, J., Gandal, N., 2022. The Microeconomics of cryptocurrencies. J. Econ. Lit. 60 (3), 971–1013.
Haykir, O., Yagli, I., 2022. Speculative bubbles and herding in cryptocurrencies. Financ. Innov. 8 (1), 78.
Howell, S.T., Niessner, M., Yermack, D., 2020. Initial coin offerings: financing growth with cryptocurrency token sales. Rev. Financ. Stud. 33 (9), 3925–3974.
Huberman, G., Leshno, J.D., Moallemi, C., 2021. Monopoly without a monopolist: an economic analysis of the Bitcoin payment system. Rev. Econ. Stud. 88 (6), 3011–3040.
Katz, M.L., Shapiro, C., 1985. Network externalities, competition, and compatibility. Am. Econ. Rev. 75 (3), 424–440.
Katz, M.L., Shapiro, C., 1986. Technology adoption in the presence of network externalities. J. Polit. Econ. 94 (4), 822–841.
Katz, M.L., Shapiro, C., 1994. Systems competition and network effects. J. Econ. Perspect. 8 (2), 93–115.
King, T., Koutmos, D., 2024. ESG crypto coins: speculative assets, or, the future of green money? Rev. Quant. Finan. Acc. 1–40.
Lee, K., Jeong, D., 2023. Too much is too bad: the effect of media coverage on the price volatility of cryptocurrencies. J. Int. Money Financ. 133, 102823.
Li, J., Mann, W., 2025. Digital tokens and platform building. Rev. Financ. Stud. 38 (7), 1921–1954.
Li, T., Shin, D., Wang, B., 2023. Cryptocurrency Pump-and-Dump schemes. SSRN Working Paper.
Liu, Y., Tsyvinski, A., 2021. Risks and returns of cryptocurrency. Rev. Financ. Stud. 34 (6), 2689–2727.
Liu, Y., Tsyvinski, A., Wu, X., 2022. Common risk factors in cryptocurrency. J. Financ. 77 (2), 1133–1177.
Lucey, B.M., Vigne, S.A., Yarovaya, L., Wang, Y., 2022. The cryptocurrency uncertainty index. Financ. Res. Lett. 45, 102147.
Lyandres, E., Palazzo, B., Rabetti, D., 2022. Initial coin offering (ICO) success and post-ICO performance. Manag. Sci. 68 (12).
Makarov, I., Schoar, A., 2020. Trading and arbitrage in cryptocurrency markets. J. Financ. Econ. 135 (2), 293–319.
Malinova, K., Park, A., 2023. Tokenomics: when tokens beat equity. Manag. Sci. 69 (11), 6568–6583.
Pagnotta, E.S., 2022. Decentralizing money: Bitcoin prices and blockchain security. Rev. Financ. Stud. 35 (2), 866–907.
Polyzos, E., Rubbaniy, G., Mazur, M., 2024. Efficient market hypothesis on the blockchain: a social-media-based index for cryptocurrency efficiency. Financ. Rev. 59 (3), 807–829.
Polyzos, E., Youssef, L., 2025. Investigating the impact of global events on cryptocurrency performance: a big data event study approach. J. Int. Money Financ. 103375.
Prat, J., Danos, V., Marcassa, S., 2025. Fundamental pricing of utility tokens. Management Science. Forthcoming.
Rognone, L., Hyde, S., Zhang, S., 2020. News sentiment in the cryptocurrency market: an empirical comparison with Forex. Int. Rev. Financ. Anal. 69, 101462.
Sakkas, A., Urquhart, A., 2024. Blockchain factors. J. Int. Financ. Mark. Inst. Money 94, 102012.
Saleh, F., 2021. Blockchain without waste: Proof-of-stake. Rev. Financ. Stud. 34 (3), 1156–1190.
Sapkota, N., 2022. News-based sentiment and bitcoin volatility. Int. Rev. Financ. Anal. 82, 102183.
Schilling, L., Uhlig, H., 2019. Some simple Bitcoin economics. J. Monet. Econ. 106, 16–26.
Shams, A., 2020. The structure of cryptocurrency returns. SSRN. http://www.ssrn.com/abstract=3604322.
Shen, D., Urquhart, A., Wang, P., 2022. Bitcoin intraday time series momentum. Financ. Rev. 57 (2), 319–344.
Shen, D., Urquhart, A., Wang, P., 2020. A three-factor pricing model for cryptocurrencies. Financ. Res. Lett. 34, 101248.
Sockin, M., Xiong, W., 2023. A model of cryptocurrencies. Manag. Sci. 69 (11), 6417–7150.
Urquhart, A., Yarovaya, L., 2023. Cryptocurrency research: future directions. Eur. J. Financ. 1–6.
Wu, F.L., Wang, Y.S., Wan, Y.F., Wang, M.H., 2025. Does Investor attention Drive Cryptocurrency Markets? Insights from Network Connectedness and Portfolio applications. J. Int. Money Financ. 103391.
Yousaf, I., Yarovaya, L., 2022a. Herding behavior in conventional cryptocurrency market, non-fungible tokens, and DeFi assets. Financ. Res. Lett. 50, 103299.
Yousaf, I., Yarovaya, L., 2022b. The relationship between trading volume, volatility and returns of non-fungible tokens: evidence from a quantile approach. Financ. Res. Lett. 50, 103175.