International Journal of *Financial Studies*

MDPI

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Blockchain Tokens, Price Volatility, and Active User Base: An Empirical Analysis Based on Tokenomics

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Abstract: Blockchain tokens have accumulated tremendous market value but remain highly controversial, given their price volatility and seemingly speculative nature. Ironically, this very characteristic can foster token retention as users wait for occasions of appreciation. In this paper, we conduct an empirical analysis with 58 tokens in two steps: first, an investigation of the drivers of user activity and token price volatility using a new blockchain token classification framework, searching for possible tokenomics links. Our findings suggest that there is an intrinsic relationship between the way tokens are used as a means of exchange and how token usage dynamics influence user engagement oppositely to market stability. Only some features, such as earning potential and voting rights, foster token-holding strategies, while only Ethereum ecosystem membership has positive effects on price volatility. Second, we analyze the direct relationship between price volatility and active users. Results show that, on average, a 10% increase in volatility is related to a decrease in active addresses ranging between 3.96% and 5.88%. The finding is supportive of the hypothesis that token price volatility may be treated as an opportunity to increase token retention.

Keywords: tokens; blockchain; price volatility; active user base; tokenomics

JEL Classification: G11; G40; O31

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Citation: Moncada, Roberto, Enrico Ferro, Maurizio Fiaschetti, and Francesca Medda. 2024. Blockchain Tokens, Price Volatility, and Active User Base: An Empirical Analysis Based on Tokenomics. *International Journal of Financial Studies* 12: 107. https://doi.org/10.3390/ijfs12040107

Academic Editor: Marwa Elnahass

Received: 20 August 2024
Revised: 28 September 2024
Accepted: 21 October 2024
Published: 23 October 2024

1. Introduction

The ecosystem of projects based on blockchain technology has dramatically expanded and diversified since the first implementation of this foundational technology as an innovative solution to the double-spending problem (Chohan 2021), realizing a disintermediated peer-to-peer cash system called Bitcoin (Nakamoto 2008). The flexibility of blockchain tokens has enabled this system's enlargement, making blockchain technology's benefits applicable to a multitude of contexts. However, while the existence of tokens in general and digital tokens, in particular, is not new, the speed with which cryptographic tokens are being deployed and issued signals how these tools could represent a major application of blockchain networks (Voshmgir 2019). This paper only deals with the last type of tokens—those developed within blockchain infrastructures and throughout the text; we refer to them as blockchain(-based) tokens (or simply tokens) and digital assets. To avoid misunderstanding, we do not use standard designations in use within the terms of computer science: "coin" versus "token" to distinguish purely trader cryptocurrencies on their platform from some other place.

Blockchain-based tokens can be studied along two main dimensions: the functions they perform and the value they represent. Concerning the former, a token can be seen as a tool able to support coordination among actors within a regulated environment to achieve a network objective function driven by a pre-designed incentive system (Freni et al. 2022). Functionality, on the other hand, does not have a univocal definition as it relies on what the token represents. A token is mainly the value it embeds, but given the increasing diffusion of blockchains, it is also much more. For instance, a token can provide access to services or grant voting rights and it has the unique ability to represent almost any asset in digitalized form (e.g., gold ingots, right to discount, pieces of an apartment). Although digital assets are not new, blockchain-based tokens enable valuable advantages that pave the way for new business opportunities, new use cases, and even innovative asset types (e.g., NFTs).

According to CoinMarketCap[1], as of February 2024, 14 years since the inception of the Bitcoin protocol, an ecosystem of almost ten thousand publicly traded digital assets is available in the market, reaching a global crypto market cap of around $2.1T. With substantial capital inflow, the blockchain market has been expanding, and the user base, as well as applications, has been increasing in multiples. Hence, it has become more versatile than before. But, at the same time, the market is filled with skepticism toward the considerable price fluctuations of blockchain assets. This skepticism often correlates with speculative trading activities that can be destabilizing if the speculative fervor has extremes on either the buy side or the sell side (Algieri 2012).

However, as a relatively young industry, the investment profile of blockchain-based tokens is similar to startup equity with the advantage of high liquidity and price discovery from the start (Malekan 2022). The absence of intermediaries and automating operations (issues, trades, and transfers) enabled by the underlying blockchain infrastructures make the inherent tokens' volatility less problematic than that for traditional financial instruments (such as startup equity). Token volatility goes beyond mere speculation, a continued and sometimes exaggerated reaction to internal and external events related to their investments by investors. That is because of the volatility that characterizes the markets, which inherently lifts the perceived risk levels; therefore, this volatility is not entirely detrimental but may be seen as an opportunity where investors value the windows of appreciation offered by tokens. To this end, price fluctuations can give rise to token-holding strategies. It can incentivize investors to hold tokens in their wallets for a long time with the hope of future gains. In this regard, it can contribute to reducing velocity due to its holders being more inclined to wait through markets rather than trade repeatedly.

Therefore, this paper investigates the relationship between token price volatility and the active user base (measured through the count of active addresses) to check whether increased volatility can trigger token-holding strategies by reducing transactional activities. Considering the wide-ranging features across tokens, we develop a two-stage empirical analysis. We first analyze the relationship between token characteristics and the two main variables of this research, i.e., price volatility and active addresses focusing on the economic system governing the creation, distribution, and use of tokens in a blockchain network (also known as tokenomics, which includes token issuance, distribution, utility, functionalities, and governance, shaping the ecosystem's rules and incentive mechanisms). Subsequently, the second step involves the empirical study of the effect of the price volatility of tokens on the number of active addresses in the blockchain infrastructures under investigation to observe whether price fluctuations can enlarge users' investment time horizons.

Our findings reveal that specific token features, such as earning potential and voting rights, tend to diminish the active user base of blockchain networks, promoting mechanisms for token retention. Conversely, the number of active addresses is positively influenced by the tokens' capacity to serve as a medium of exchange. This positive correlation indicates that users tend to engage more with networks where tokens can be easily traded or used for transactions. Tokens used as a medium of exchange also correlate negatively with price volatility, suggesting their role in fostering market stability. However, tokens developed on the Ethereum blockchain show a positive relationship with price volatility, potentially due to the platform's dynamic environment. The analysis reveals an underlying connection between the number of active addresses and price volatility within the tokenomics framework. This connection is mediated by the use of tokens as a medium of exchange, which has differing effects on these two variables, implying that token usage dynamics significantly influence user engagement and market stability in opposite ways. On the other hand, in the second analysis, we find a statistically significant negative impact of token price volatility on the count of active addresses. This supports the hypothesis that market perception of price volatility may not always be negative; rather, it can slow down network activity by reducing transactions and prompting mechanisms for retaining digital assets to capitalize on potential appreciation opportunities.

This paper makes a significant contribution by exploring an unpaved investigation path: the empirical relationship between token price volatility and active address count within blockchain platforms. Our study is grounded in a preliminary empirical investigation that examines the tokenomics links between these variables, considering the diverse range of functionalities that tokens can encompass. By delving into this uncharted territory, our research sheds light on the intricate dynamics of blockchain ecosystems and offers valuable insights into the factors influencing market behavior and user engagement.

The remainder of this paper is organized as follows. Section 2 presents a review of the literature. Section 3 discusses the token classification framework used to identify token features. Section 4 describes the data used in the analysis and the descriptive statistics. Section 5 presents the empirical strategy employed in this work. The results of this study are presented in Section 6. Finally, Section 7 concludes this paper.

2. Literature Review

This study contributes to the expanding economic literature on blockchain technology. While previous research has not empirically examined the direct relationship between token price volatility and active addresses, nor conducted any empirical tokenomics analysis between the two variables, many papers in the blockchain tokens literature have explored related topics such as volatility, user adoption, network activity, and token pricing. Chen et al. (2020) find that high user adoption and stable token prices are linked to reduced platform productivity volatility. They also find that the token price is often more volatile than the productivity process, and the token price can be stabilized by productivity volatility and user base adoption. Bakhtiar et al. (2023a) investigate the impact factors and sentiments on token values. Their findings suggest that Google search interest in cryptocurrency is crucial when choosing the appropriate token type. While consensus mechanism and ICO significantly affect tokens without stablecoins, other fundamental factors, such as supply type and smart contracts, do not significantly influence cryptocurrency value. Sareen (2023) identifies various on- and off-chain factors that can affect token volatility, including the percentage of tokens dedicated to private sales and rewards, the length of a token's vesting period, and the token's market capitalization. Mikhaylov et al. (2021) discuss how token volatility is important in terms of financial instruments for hedging traditional assets, as well as in terms of pricing.

Further research on token price volatility has identified several key factors. Al Guindy (2021) finds that increased investor attention, as measured by social media activity, is associated with higher price volatility. Katsiampa (2019) further explores this, showing that the conditional variances of major tokens (BTC, ETH, LTC, XLM, and XRP) are influenced by previous errors and conditional volatility, with asymmetric past shocks having a significant impact. Rasheed and Ali (2022) extend this work by demonstrating interdependencies in the volatility of top blockchain tokens during global health crises. In addition, Conrad et al. (2018) highlight the influence of external factors, such as the S&P 500 realized volatility, on long-term Bitcoin volatility.

For what concerns, instead, blockchain network activity and user adoption, Parino et al. (2018) attempt to characterize the adoption of the bitcoin blockchain by country, identifying several socioeconomic indexes such as the GDP per capita, freedom of trade, and the Internet penetration as key variables correlated with the degree of user adoption. In a blockchain economy, the incentive of record keepers and the activity of blockchain users interact with each other through general equilibrium effects. In this context, Aoyagi and Adachi (2018) show that multiple equilibria can arise in which collective deviation of miners (e.g., fork) can deteriorate the blockchain's efficiency and consumers' welfare. Further research highlights a range of factors that influence the adoption and use of blockchain technology. Gharehdaghi and Kamann (2023) highlight the importance of strategic information insertion, cost–benefit analysis, and external drivers in the decision-making process. Raddatz et al. (2023) emphasize the role of threat severity, threat susceptibility, awareness, and inertia in shaping consumers' perceptions of blockchain benefits. Mnif et al. (2021) underscore the significance of security, shareability, and decentralization in driving user interest and acceptance. Jevremović et al. (2022) further explore the impact of interactivity in blockchain technologies on user behavior, with a focus on the differences between interactive and non-interactive technologies. These studies collectively suggest that a combination of technical, organizational, and user-related factors determine the active user base of blockchain technology. Bakhtiar et al. (2023b) discuss the use of Metcalfe's Law to evaluate the relationship between token prices and the number of active wallet addresses, transactions, and circulations. They examine the network effects and store-of-value characteristics of a wide range of tokens. Their findings indicate that stablecoins have comparable daily volatility to gold, while only mature cryptocurrencies strongly correlate with gold. Finally, Shen et al. (2023) integrate model uncertainty into the theory on dynamic adoption and valuation of token-based platforms. Their research reveals that individuals with distorted beliefs exhibit greater hesitation, resulting in a reduced user base for digital currency platforms. Furthermore, their results highlight how ambiguity exacerbates the volatility of the tokenized economy's user base.

The field of tokenomics, which explores the structure and features of tokens within blockchain ecosystems, has received limited attention in empirical research. Only a few studies have delved into this area, with Lo and Medda (2020) standing out as the sole comprehensive investigation into the relationship between token functions and market prices. In this study, they take a systematic approach, developing a stepwise analysis based on four hypotheses to understand the factors influencing the market value of tokens. They leverage a classification framework to isolate the effects of token functions, features, and distribution characteristics. By systematically testing these hypotheses, they provide valuable insights into the complex dynamics that drive token valuation within blockchain networks. In this context, this paper aims to make a cross-domain contribution to the strands of literature presented so far, pursuing an unpaved path of investigation through an empirical analysis of the relationship between token price volatility and active address count within blockchain platforms. This analysis is grounded on a preliminary empirical investigation concerning the tokenomics links between tokens price volatility and active address count in light of the vast spectrum of functionalities tokens can perform, connecting this paper also to the empirical tokenomics literature initiated by Lo and Medda (2020).

3. Token Classification

The value that blockchain-based tokens represent cannot be uniquely defined and does not necessarily have an inherent, standalone definition. Therefore, it is not possible to represent blockchain tokens as a homogeneous class of digital assets. All the tokens that are created on blockchain platforms have characteristics that are specific to the achievement of well-defined purposes and, as such, they do not possess an intrinsic fixed value. To understand whether these characteristics play a role in certain market dynamics of these tokens, it is necessary to categorize them with respect to the functions they can perform. Token features represent a crucial dimension of our research, and they are essential to empirically test their effect (if any) on price volatility and the count of active addresses to check whether any underlying tokenomics connection exists between these two metrics.

To date, a substantial amount of token taxonomies and classifications have been proposed. One of the most extensive investigations on the subject is given by Oliveira et al. (2018), combining a thorough literature review with information gathered from 16 interviews with practitioners and specialists. The final classification describes the technical characteristics of tokens as well as their business-related elements based on 13 distinct metrics. In addition, they delineate eight token archetypes by examining recurrent feature patterns after mapping 18 tokens. It is also worth mentioning that this work is grounded on a number of previous classifications. Among others, Mougayar (2017) contributes significantly to understanding the nature of tokens. The author proposes a three-dimensional classification based on the tokens' role, features, and purpose. This framework mainly focuses on the business-related features of tokens, specifically mentioning how they are tied to the business model of the token issuer and the benefits that token holders receive. Additionally, Euler (2018) groups tokens into five categories: technological layer, underlying value, legal status, purpose, and utility. This framework aims to examine a single token from multiple angles simultaneously and is the first attempt to capture and summarize the multi-faceted nature of tokens. As mentioned above, Lo and Medda (2020) also develop a token characteristics framework, identifying in the analysis token functions (payment, utility, asset, and yield), token features (stake rewards and medium of exchange), and token distribution (only for insiders and firms, and only for miners and service providers).

In the framework of the taxonomies and token classifications identified in the literature, a wide range of methodologies and approaches are adopted, considering specific perspectives of the tokenization phenomenon. However, for the purpose of this paper, the classification of tokens must be conducted in a context-free fashion, seeking to capture as much detail as possible about the token functionalities being analyzed. For this reason, we adopt the morphological token classification framework developed by Freni et al. (2022). They propose a classification framework to capture an all-around representation of the tokenization phenomenon, providing a tool for a token's extensive and complete description. In particular, this paper offers a valuable methodology for both theoretical and practical applications in the field of tokenomics, building upon previous context-specific works. They propose a structure characterized by 14 dimensions, grouped in three domains, and almost 5 million possible configurations, creating an extensive morphological field (see Appendix A, Figure A2).

The selection criterion for the dimensions that are included within the token classification strategy of this paper relies on the choice of token characteristics that determine their functionalities. Blockchain-based tokens have appreciation capacity and can be used as a store of value, as such we focus on the dimensions of *incentive enablers* and *incentive drivers* (see Appendix A, Figure A2). Figure 1 shows the characteristics of the tokens analyzed in this research as a result of the adaptation of the work conducted by Freni et al. (2022) about the classification framework discussed above, to be applied in the empirical analysis explained in Section 5.

The boxes on the left-hand side of the figure represent the main functions that the tokens analyzed in this research can perform, with multiple functions often co-existing within a single token, making these characteristics not mutually exclusive. Only the *utility* and *governance participation* functions require further breakdown to detail related token features. The middle boxes identify the different rights associated with utility tokens and governance participation. Utility tokens grant access to various rights, categorized into three cases represented by the light blue boxes on the right-hand side of Figure 1. These include access to services or content through staking, discounts on services or content, and rewards for contributions to the ecosystem. in Appendix A, Figure A1 provides a detailed token classification scheme, outlining the criteria for identifying token features.

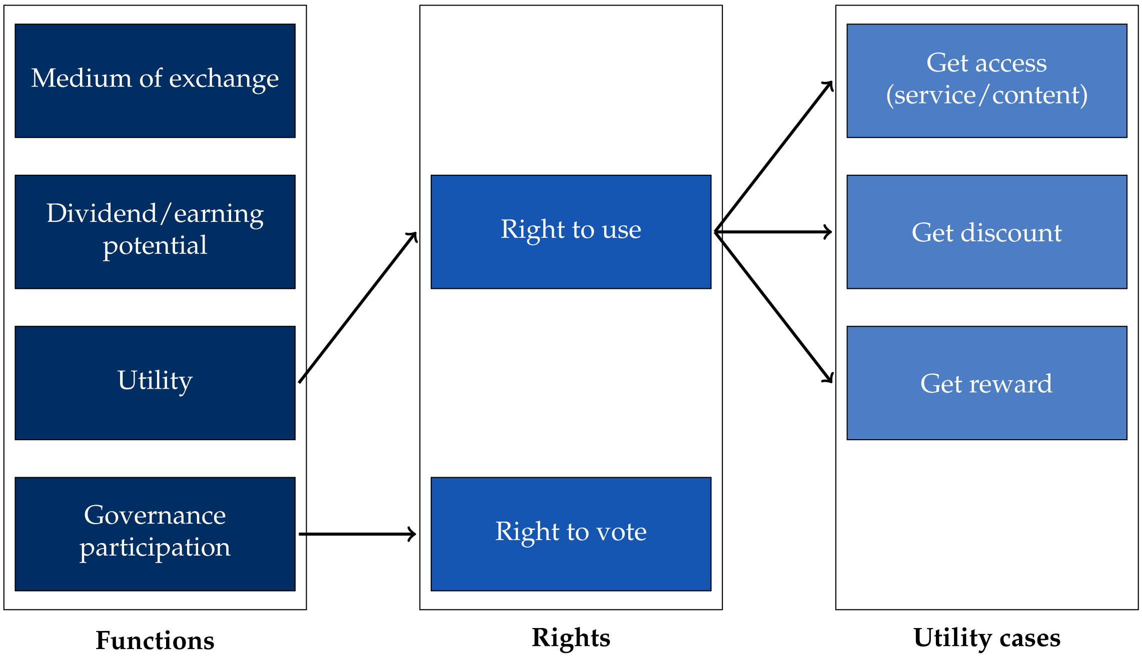

Figure 1. Token features classification.

4. Data

The primary source of data for this work is Coinmetrics.io[2], which is one of the leading providers of crypto financial intelligence granting access to network data, market data, index, and network risk solutions. The use of these data is standard practice in the literature (Bhambhwani et al. 2021; Chen and Irresberger 2022; Liu and Tsyvinski 2021). In particular, Coinmetrics.io only provides data based on reputable exchanges using 35 criteria to screen out illiquid and unreliable exchanges (Urquhart 2022). The database that Coinmetrics.io gives access to counts more than 250 tokens.

Pursuing the scope of the research, we have focused only on those tokens with available data that were compatible with this study's objective. Accordingly, to select the tokens for our analysis, we focused on those that derive their value strictly from market supply and demand, excluding tokens whose value is influenced by external factors, such as physical assets (e.g., gold) or financial instruments (e.g., stablecoins, wrapped tokens). This process ensures that the tokens analyzed have the potential for price appreciation and serve as a store of value. As a result, we downloaded data about 58 blockchain-based tokens on 25 january 2023. Note that the data-gathering approach that has been performed does not threaten to generate any selection bias either, given that all the blockchain-based tokens whose data were available on Coinmetrics.io have been included in the dataset, ensuring that no tokens with values derived from market matching between supply and demand were omitted. In Appendix A, Table A1 presents the list of the tokens included in the dataset, together with information related to the number of observations per token, their date of birth, the underlying blockchain infrastructures, and the features associated with the functionalities they can perform (identified by answering the questions displayed in Figure A1).

The information made available by Coinmetrics.io includes daily observations of the sum count of unique addresses that were active (i.e., either as a recipient or originator of a ledger change) used as a proxy of the volume of the active user base in the networks. The data also include information about token price volatility, measured as the standard deviation of the daily natural log returns over 30 days. In addition, the dataset contains daily observations about token prices denominated in USD, return on investment (ROI) for the selected digital assets assuming a purchase 30 days prior, the sum count of transfers measured in native units of tokens from one ledger entity to another distinct ledger entity, and the average transaction size denominated in USD. Some of the metrics used in this research (i.e., tokens price volatility and ROI) are calculated as daily observations of rolling averages over 30-day periods.

Therefore, to homogenize the analysis time interval, all the variables used in this research contain daily observations considered over time intervals of 30 days. In other words, 30-day rolling averages have been applied to smooth short-term volatility and focus on more significant trends. The choice of the 30-day time interval is standard in the literature and allows us to capture the medium-term dynamics of both user activity and price volatility. As a result, the final sample contains a total of 93,923 daily observations spread across 58 tokens, with each token having a varying number of time intervals depending on its creation date and availability of historical data. This approach ensures that all available data for the tokens are included, and the analysis reflects a comprehensive evaluation of their performance over time. The result is an unbalanced panel that covers the period between 17 August 2010 and 24 January 2023. The reason behind the unbalanced nature of the data stems from the fact that each blockchain token was created at a different time. Therefore, even if Coinmetrics.io gives access to historical data covering almost all tokens' lifespans, the number of observations is, by definition, different for each token and inherently related to their establishment. In terms of token lifespan duration, the average number of observations per token is approximately 1619, corresponding to 4.44 years. The range's upper bound is represented by BTC (launched in January 2009) with 4544 observations, translating into 12.45 years. The lower bound, instead, is represented by ICP (launched in May 2021) with 594 observations, equivalent to 1.63 years. Note that some tokens present missing data points within the period under analysis, thus explaining the difference in the number of observations per token with reference to their date of establishment (for more details about tokens lifespan, see Table A1). Note that the number of observations indicated in Table A1 represents the number of 30-day rolling averages we can observe in the dataset for each token. Table 1 presents the descriptive statistics regarding the variables used in this research. The information contained in Table 1 shows the wide inherent variability of the metrics included in the dataset, driven by the considerable heterogeneity of the data in terms of tokens and their characteristics.

Table 1. Descriptive statistics for the sample of 58 blockchain-based tokens.

	Mean	SD	Min	25th	50th	75th	Max
Active addresses	61,536.031	198,427.717	5.700	231.400	1522.700	23,921.400	2.453M
Price volatility	0.064	0.032	0.000	0.043	0.057	0.077	0.394
Token price, USD	718.347	4526.331	0.001	0.135	1.527	20.532	80,554.717
ROI	12.512	98.643	−96.465	−21.199	−2.597	22.012	6502.928
Transfers count	377,855.964	3.976M	3.200	362.333	2548.367	39,814.133	75.428 M
Avg TX size, USD	193,080.890	6.652M	0.428	704.144	3245.000	13,974.690	364.468 M

Note: The source of data is Coinmetrics.io. Where required, values are expressed in M = millions of units. All the variables displayed in the table refer to time intervals of 30 days. The sample counts 93,923 daily observations for 58 blockchain-based tokens.

In addition, the sample considered is also noticeably representative. Figure 2 shows the cumulative share of market dominance of the 58 tokens included in the dataset (in blue) relative to the rest of the tokens in the market (in orange). Data on market dominance of the digital assets included in the dataset are made available by CoinMarketCap, and the information on individual token shares was obtained on the same day as the data from Coinmetrics.io (i.e., 25 January 2023). The market share accounted for by the 58 tokens located within the sample amounts to more than 75%. As of January 2023, according to CoinMarketCap, the blockchain-based token market counts more than 9000 digital assets. However, most of these are still in their inception stage, with very low liquidity (due to a limited market) and little data availability.

For this reason, although our dataset contains a restricted number of digital assets (at least compared to the totality of tokens in the market), it is actually possible to claim that, based on the aggregate market dominance of the 58 tokens available to us, the dataset used in this research is representative of the current market. In addition, Figure 2 displays the distribution of the 58 blockchain-based tokens with respect to their features, as defined in Section 3, to give a graphic idea of the composition of the dataset in terms of token functionalities (for more details about individual token functionalities, see Table A1). In this case, we also include a category dedicated to Ethereum blockchain-based tokens, given that many tokens issued in the marketplace exploit the Ethereum infrastructure. In this regard, additional information has been added to the initial dataset by taking advantage of the framework defined in Section 3 in order to classify the 58 tokens.

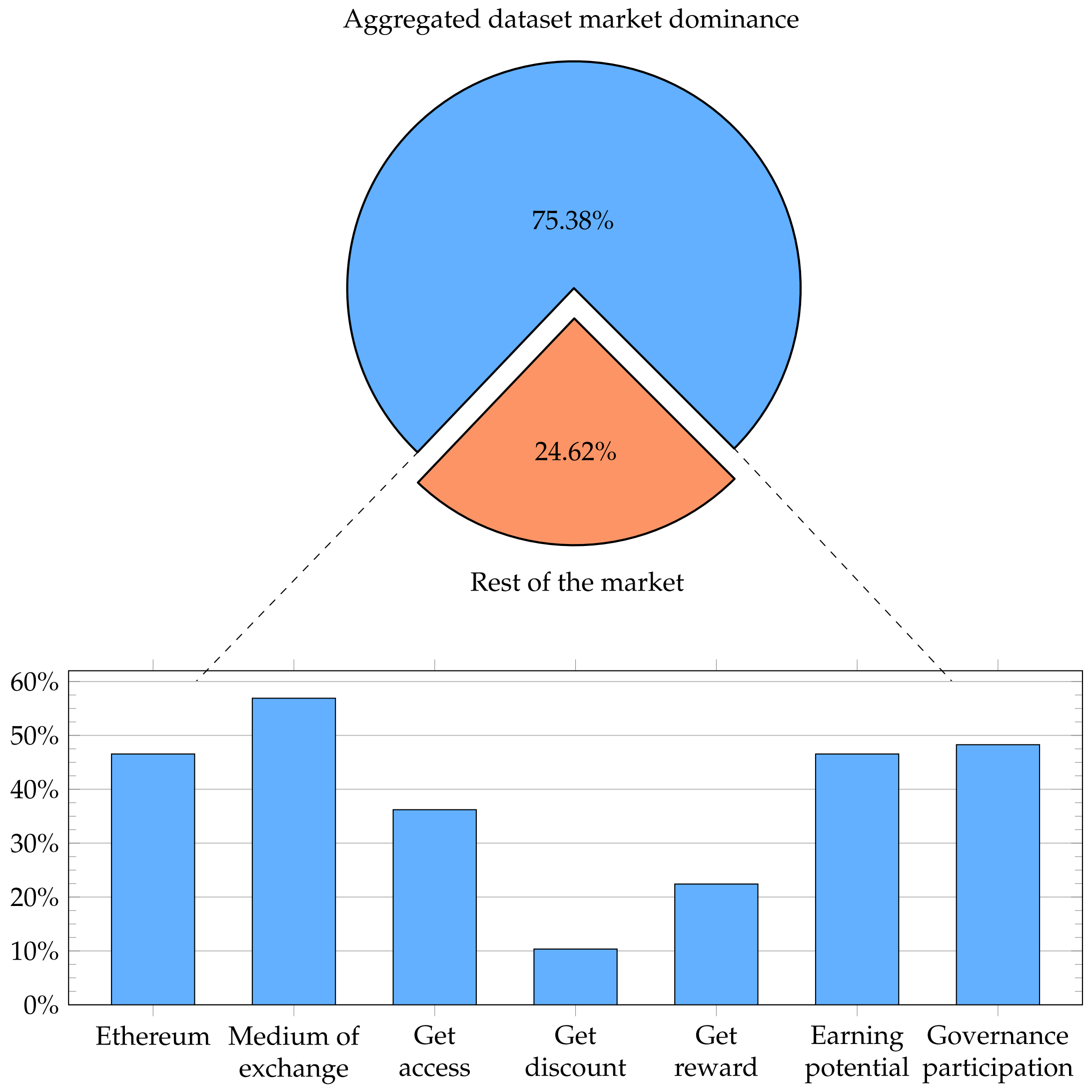

Figure 2. Dataset market dominance and distribution per token features.

Table 2 shows the descriptive statistics related to the token dummy variables deriving from token classification and used in our empirical analysis to investigate the effect of token features on their price volatility and the count of active addresses in the networks. It provides the name of the dummies, a basic description of them, together with the frequency of each feature and its share with respect to the total number of tokens. Additionally, in the last column, the table displays the share of the features with respect to the sample size (i.e., 93,923 daily observations). Considering that the panel is unbalanced, the information related to the sample shares allows us to observe whether the dataset is skewed toward specific features. We can observe that, although the panel distribution does not perfectly match the distribution of token characteristics, there is no relevant inward asymmetry.

Table 2. Statistics of token dummies.

Token Dummy	Description	Number	Token Share	Sample Share
Ethereum	Tokens based on the Ethereum blockchain	27	46.55%	35.49%
Medium of exchange	Tokens used to intermediate the exchange of services/goods	33	56.90%	65.88%
Utility—Right to use		**25**	**43.10%**	**35.47%**
Get access (service/content)	Tokens grant access to services/content in the ecosystem	21	36.21%	33.23%
Get discount	Tokens allow to benefit from discounts on services/content	6	10.35%	6.26%
Get reward	Tokens reward users for their contribution to the ecosystem	13	22.41%	18.99%
Dividend/earning potential	Token holders can benefit by staking/holding tokens	27	46.55%	36.70%
Governance participation				
Right to vote	Tokens allow to influence the policy making process of the ecosystem	28	48.28%	37.35%

All the dummy variables shown in Table 2 come from the classification depicted in Figure 1 plus an additional one related to Ethereum blockchain-based tokens. In this case, we can note that almost 47% of the tokens are based on the Ethereum blockchain, highlighting the heterogeneity of the dataset. Indeed, as previously mentioned, many of the tokens available in the market are developed on the Ethereum blockchain. Since all the other tokens included in the dataset are developed on standalone blockchain solutions, the identification of this characteristic through the generation of a specific dummy variable is beneficial for the analysis by investigating whether belonging to the Ethereum ecosystem plays a role in the activity of the user base and the price volatility of tokens (for more details about tokens' underlying blockchain infrastructure, see Table A1). Concerning the other dummy variables, almost 57% of the tokens at our disposition can be considered a medium of exchange, as they are accepted to intermediate exchanges inside or outside blockchain environments. Utility tokens have been divided into three categories, each granting a specific right to use the token. The bold line in Table 2 summarizes utility tokens, i.e., digital assets that offer one or more utilities among the three identified. Only six tokens (10.3%) give access to discounts. At the same time, around 22% of them are allowed to be rewarded when contributing to the ecosystem, and about 36% of the tokens allow access to content within the ecosystem to token holders.

In summary, around 43% of tokens (i.e., 25 out of 58) can be considered utility tokens, giving access to one or more rights to use the token within their blockchain ecosystem. When a token can be staked (or held) to receive a financial benefit (often in the form of the token itself), then the dummy variable *dividend/earning potential* takes the value 1. The tokens granting access to earning processes are 27 out of 58, corresponding to almost 47% of the digital assets analyzed. Finally, we identified 28 *governance participation* tokens, i.e., tokens that grant voting rights to token holders, allowing them to influence the decisions that shape the rules of the blockchain ecosystem. Every token in the dataset has at least one of the functionalities identified in the token classification framework. Most of them perform more than one functionality and, as such, are counted several times in different categories. This also implies that the tokens identified in a specific category are not necessarily the same as another one, i.e., there is some degree of category-to-category overlapping, even if not perfectly matching among features.

5. Empirical Strategy

The empirical analysis of this paper is performed in two steps. In the first one, we assess the drivers of token price volatility and the active user base of blockchains. In this way, we are able to observe whether price volatility and active user base are connected through the underlying tokenomics (with reference to the token dummies that identify token functionalities). In the second step, we investigate the effect of price volatility on the count of active addresses in order to understand whether price volatility can trigger token-holding strategies by reducing transactional activities. Although interconnected, the two analysis steps are methodologically separate and performed at different stages, given the structure of the models explained in what follows.

Preliminary to any empirical analysis, we test for the stationarity of our panels. We implement Fisher-type tests (Choi 2001) for unbalanced panels to check for unit roots. The results of these tests allow us to reject the null hypothesis for all the variables, including one to four lags, meaning that all panels appear stationary. Consequently, there is no need to include any lag in the regressions. Table A2 in Appendix A shows the results related to one of the four statistics (i.e., inverse chi-squared statistic) generated by the Fisher-type tests. The other results are available upon request. Then, Table A3 in Appendix A shows the correlation coefficient matrix regarding all the variables used in the analysis (including token dummies).

Concerning the empirical analysis, we perform a pooled OLS regression for the first step, as in Lo and Medda (2020). In particular, this model allows for overcoming the challenge imposed by the unbalanced form of the panel dataset, an attribute that some alternative approaches cannot address. Feasible Generalized Least Squares (GLS) modeling, for instance, permits the direct specification of auto-correlation and heteroskedasticity across panels. However, in this first step of the analysis, it is precluded in our case, as modeling for auto-correlated errors necessitates equally spaced data, and modeling for cross-sectional errors mandates balanced panels. Another alternative to pooled OLS when dealing with unbalanced panel data is represented by fixed effects (FE) and random-effects (RE) models. However, as explained below, they are unfeasible for constructing our models, at least in the first step of the analysis. Consequently, the flexibility of OLS regression proves advantageous in accommodating the structure of our panel data.

Therefore, in our pooled OLS settings, the dependent variable is, in one case, the sum of unique addresses that have been active (i.e., that have sent funds in transactions at least once during the time interval taken into consideration) and, in the other case, the tokens price volatility, measured as the standard deviation of log returns. On the other hand, independent variables include the set of dummies deriving from the token classification analysis carried out in Section 3, plus a dummy for identifying Ethereum-based tokens. In particular, the six token dummies identifying token features come from each final branch of the horizontal tree depicted in Figure 1. Since token features are not mutually exclusive, the related dummies are all included within the econometric models without the risk of causing multicollinearity. Moreover, as mentioned above, implementing FE models is not feasible. Otherwise, all results for dummy variables would be omitted due to the estimation process of the FE models. However, this does not prevent us from including in the analysis time-fixed effects to take into account potential herding behaviors, sentiments, and other time-related features common to crypto markets. Consequently, the empirical model related to the effect of token features on the count of active addresses is formally expressed in Equation (1).

$$\begin{aligned} Act\ Address\ Cnt_{it} = {} & \beta_0 + \beta_1 Earn_i + \beta_2 Vote_i + \beta_3 Access_i + \beta_4 Discount_i \\ & + \beta_5 Reward_i + \beta_6 Exchange_i + \beta_7 Ethereum_i + \gamma' \mathbf{X_{it}} + \theta_t + \epsilon_{it} \end{aligned} \tag{1}$$

In Equation (1), $Act\ Address\ Cnt_{it}$ is the average count of unique addresses that have been daily active (i.e., that have performed transactions) over 30-day time intervals, and β_0

is the constant term. Then, the model contains a series of seven dummies that identify token features. Four of these dummies refer to precise characteristics of the token, i.e., whether the token has dividend/earning potential ($Earn_i$), if it allows governance participation ($Vote_i$), whether it is used as a medium of exchange ($Exchange_i$), and if it is based on the Ethereum blockchain ($Ethereum_i$). The remaining three dummy variables refer to utility tokens, i.e., tokens that can be used to obtain access to service/content on the platform ($Access_i$), to obtain discounts for service/content within the ecosystem ($Discount_i$), and to obtain a reward for contributing to the blockchain platform ($Reward_i$). Concerning $\mathbf{X_{it}}$, it represents a vector of covariates, including the log of token price denominated in USD, the ROI, the log of transfers count, and the log of average transactions size denominated in USD. The coefficients β_1 to β_7 measure the marginal effects of each token feature on the active address count, while γ' is a vector of coefficients (γ_1 to γ_4) capturing the effects of the covariates contained within $\mathbf{X_{it}}$ on the dependent variable. Finally, θ_t are time-fixed effects, and ϵ_{it} is the error term (with mean zero and unit variance, by the construction of the model) clustered at the token level.

On the other hand, the model related to the effect of token features on their price volatility is reported in Equation (2).

$$\begin{aligned} Volatility_{it} = \beta_0 + &\beta_1 Earn_i + \beta_2 Vote_i + \beta_3 Access_i + \beta_4 Discount_i \\ &+ \beta_5 Reward_i + \beta_6 Exchange_i + \beta_7 Ethereum_i + \gamma'\mathbf{X_{it}} + \theta_t + \epsilon_{it} \end{aligned} \tag{2}$$

In this case, the dependent variable is the token price volatility measured as the standard deviation of the daily natural log returns over 30 days, while the remaining model is the same as in the previous equation. In both equations, the variable subscripts i and t identify the variable's value for blockchain token i at time t. Also, in this case, standard errors are clustered at the token level. Including a significant number of parameters in the first two equations is necessary to capture the wide variety of token characteristics that may be relevant in different contexts. Each parameter accounts for specific token features or covariates that could influence volatility or user activity differently across tokens. This ensures that our model is flexible enough to capture variations in how these features impact the active address count and token price volatility, even if some parameters may be more relevant to certain tokens than others.

Beyond investigating the drivers of token price volatility and active user base, implementing the first two models allows us to examine tokenomics connections between these two variables. In other words, this first step of analysis is relevant for the continuation of the research through the second one to discern whether the relationship between the two variables investigated depends to some extent on the underlying characteristics of the tokens. The rationale behind it is that the methodology used in the second step does not allow us to isolate the effect of token features on the active address count.

Therefore, in the second step of our analysis, we investigate the relationship between the price volatility of tokens and active addresses. In doing so, we want to assess the effect that a changed perception of risk induced by a change in price volatility might have on the activity of the network. Specifically, network activity can be defined as any action performed by users of a blockchain platform that generates a change in the distributed ledger of blockchain infrastructures. In practice, this takes the form of the implementation of transactional activities, not necessarily limited to simple token exchanges between two users. For this second analysis step, we use an FE panel model, as per Equation (3).

$$Act\ Address\ Cnt_{it} = \beta_0 + \beta_1 Volatility_{it} + \eta_i + \theta_t + \gamma'\mathbf{X_{it}} + \mu_{it} \tag{3}$$

where β_0 is a constant term, η_i are token-fixed effects, and θ_t are time-fixed effects. $\mathbf{X_{it}}$ is a vector of covariates, including the log of token price denominated in USD, the ROI, the log of transfers count, and the log of average transaction size denominated in USD. The coefficient β_1 measures the marginal effect of volatility on the active address count, while γ'

is a vector of coefficients (γ_1 to γ_4) capturing the effects of the covariates contained within $\mathbf{X_{it}}$ on the dependent variable. Finally, μ_{it} is the error term clustered at the token level.

In this last specification, token-fixed effects allow to net out the impact of all those token-specific characteristics that do not change over time. These characteristics consider not only their inherent features (including the ones identified in the token classification framework) but also other factors that can be regarded as constant over time (e.g., the underlying blockchain infrastructure and its characteristics). On the other hand, time-fixed effects allow us to control unobservable time-changing factors that we could not control otherwise, which could play a role in determining the active user base in the networks. In addition, by implementing clustered standard errors in all the models at the token level, we are able to manage heteroskedasticity and within-cluster correlation. However, FE estimators and clustered standard errors do not allow us to manage the potential autocorrelation of the variables involved in our analysis. Therefore, considering that autocorrelation is usual in the case of financial time series as the volatility of asset prices, we develop a further layer of analysis connected to the second step explained above. Specifically, we deal with autocorrelation by estimating the model in Equation (3) applying a Feasible GLS estimator. In particular, FGLS offers more efficient estimators for large samples than OLS in heteroskedasticity and autocorrelation but requires balanced panels.

Consequently, to estimate Equation (3) via FGLS, we generate a balanced subsample of 30,200 daily observations from the original dataset. The balanced dataset covers the period between 31 December 2020 and 24 January 2023 for 40 blockchain tokens (implying 755 daily observations for each token). The time interval for the balanced panel has been defined by maximizing the number of observations and minimizing the loss of tokens.

Our analysis also considers potential reverse causality issues that could bias our results. Our empirical strategy, which implements an FE model in the second step, mitigates this concern by controlling for unobserved, time-invariant factors that could influence the relationship between our variables. This approach ensures that our findings more accurately reflect the actual dynamics between token volatility and user base activity. Additionally, to further isolate the direction of impact, we conduct a first-step analysis where we investigate the effects of token features on active addresses and token price volatility. This two-step approach allows us to rigorously explore the interactions between these variables while minimizing the risk of reverse causality.

6. Results and Discussion

This section presents the empirical results as the application of the methodology explained above. The estimations have been produced using Stata 18 Software[3]. Table 3 shows the results of the pooled OLS stepwise regression where the active address count is the dependent variable (see Equation (1)).

The first column refers to the row model, where only the token dummies have been included in the specification, whereas Column 5 displays the results related to the full control model. Two specific token utility features significantly impact the count of active addresses in the networks, i.e., *earning potential* and *right to vote*. These two dummy variables are statistically significant and negative in all the specifications. In this context, a negative effect can be interpreted as a decreasing activity in the network caused by an increase in the incentive for users to hold their tokens. The rationale for this result is that access to this type of service usually requires to *stake* the tokens one holds within the wallet.

Therefore, tokens that enable users to realize a profit by holding the digital assets in their wallet, as well as tokens that give access to voting rights, decrease their activity in the networks, stimulating token-holding strategies. These results are consistent throughout all the specifications. The dummy related to the use of tokens as a medium of exchange also presents significant results, but in this case, it has a positive sign. Thus, in contrast to the case regarding voting-related utilities and earning potentials, a positive correlation between active addresses and the ability to use tokens as a medium of exchange fosters users' engagement in the network. This suggests that the ease and efficiency of using tokens for transactions encourage users to participate more actively in the network, showing a significant and positive effect on active addresses. Furthermore, the statistics at the bottom of Table 3 demonstrate the models' progressively improving ability to explain the variation in active addresses. Notably, the F-statistic follows an increasing trend from the first model specification to the last, becoming statistically significant at the 1% level in the final two models. This pattern highlights the enhanced explanatory power of the models as more variables are included, particularly in relation to token characteristics and price-related factors.

Table 3. Token dummies effect on active address count.

	Dependent Variable: **Active Address Count**				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Earning potential	−66389.9 **	−66,495.9 **	−66,332.9 **	−715,38.3 **	−724,41.0 **
	(32,563.1)	(25,862.3)	(25,801.6)	(30,536.7)	(32,106.6)
Right to vote	−66,680.8 **	−54,237.2 ***	−54,405.6 ***	−53,356.2 ***	−53,383.4 ***
	(27,089.8)	(19,651.3)	(19,701.8)	(19,328.6)	(19,329.8)
Get access	−6,4654.2 **	−28,921.6	−28,835.9	−27,325.3	−25,189.3
	(30,479.0)	(26,459.1)	(26,415.9)	(24,156.5)	(24,222.1)
Get discount	31,807.4	−1720.5	−1514.6	1254.2	1199.5
	(23,879.0)	(34,435.0)	(34,361.2)	(38,753.2)	(35,202.3)
Get reward	−49,249.8	−17,532.5	−17,495.1	−16,048.4	−16,022.7
	(33,531.1)	(25,695.3)	(25,672.6)	(25,392.9)	(25,443.0)
Medium of exchange	31,107.7 *	47,850.2 ***	48,178.5 ***	45,348.1 **	45,336.0 **
	(15,622.1)	(17,630.2)	(17,710.7)	(17,450.6)	(17,451.2)
Ethereum	5374.2	−2399.2	−2476.0	−1005.2	−993.1
	(32,220.2)	(21,495.9)	(21,528.8)	(21,276.5)	(21,288.5)
(log) Token price		32,623.7 *	32,626.3 *	32,504.7 *	32,505.4 *
		(16,580.8)	(16,568.7)	(16,551.7)	(16,552.5)
ROI			−45.77 **	−44.20 **	−44.18 **
			(22.53)	(21.91)	(21.92)
(log) Transfer count				27,072.5 **	28,154.7 **
				(11,619.6)	(11,323.3)
(log) Mean TX size					4800.8
					(5614.5)
Constant	119,788.2 **	26,895.1	27,986.0	161,776.2 **	199,916.9 ***
	(51,816.4)	(49,003.2)	(49,142.2)	(61,189.5)	(74,111.4)
N Observations	93,923	93,923	93,923	93,923	93,923
N Tokens	58	58	58	58	58
Time FE	✓	✓	✓	✓	✓
R^2	0.1172	0.2602	0.2607	0.3545	0.3565
Adjusted R^2	0.1171	0.2601	0.2606	0.3544	0.3563
F	0.95	2.03 **	2.12 **	5.23 ***	5.36 ***

Note: All the variables refer to monthly time intervals. Clustered SE at the token level are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Figure 3 presents the token dummy coefficients corresponding to the fifth column of the results in Table 3, along with their respective confidence intervals. The figure highlights that earning potential, voting rights, and medium of exchange are the only statistically significant coefficients, as their confidence intervals do not intersect the zero threshold (i.e., they remain consistently above or below zero). Additionally, Figure 3 illustrates that tokens associated with earning potential and voting rights are negatively correlated with network activity, whereas serving as a medium of exchange tends to influence the active address count positively.

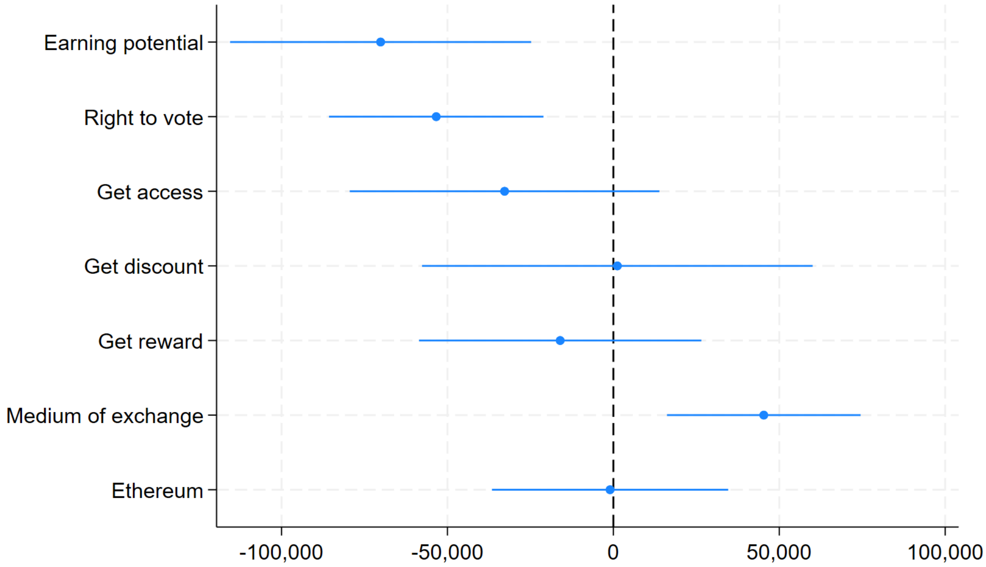

Figure 3. Token dummies effect on active address count—coefficients chart.

Moreover, regarding the results presented in Table 3 and Figure 3, it is worth mentioning that, as discussed in Section 5, the panel unit root tests we conducted to assess the stationarity of our variables provided strong evidence of the absence of non-stationarity across all key variables (see Table A2). This confirms that our data do not exhibit trends that would require de-trending. As a result, we conclude that the large coefficient sizes observed are not due to non-stationarity but rather represent the true magnitude of the relationships between token characteristics and active addresses within the model framework.

We perform the same econometric model using token price volatility as the dependent variable to observe the effect of token features and to check for potential underlying connections between active address count and price volatility with respect to token functionalities (see Equation (2)). Table 4 displays the results related to the stepwise estimation of this model. What we can observe, in this case, is that neither utility-related token features nor voting rights appear to be a statistically significant driver of price volatility. Conversely, two features show statistically significant estimates: the dummy that identifies Ethereum-based tokens and the dummy related to the use of tokens as a medium of exchange. On the one hand, the effect of the Ethereum dummy on the dependent variable is positive, meaning that tokens issued on the Ethereum blockchain tend to have higher levels of price volatility.

Considering that Ethereum is by far the most thriving blockchain ecosystem in terms of new token issuance, one of the reasons behind the results obtained in Table 4 may be (even if non-empirically tested) the youthfulness of Ethereum-based projects (excluding Ethereum itself, which represents one of the most mature blockchain platforms, founded in July 2015). Indeed, *ceteris paribus*, younger projects are generally less spread among investors. As such, price volatility may be more sensitive to transactional movements than older networks that exhibit enhanced stability both by virtue of larger user bases (i.e., a greater distribution of token units in the outside world) and greater maturity of the projects themselves. On the other hand, we find a negative and statistically significant correlation between token price volatility and the feature related to the use of the tokens as a medium of exchange. This result suggests that token usage has an impact on market stability. In particular, those tokens that facilitate trades and can be used inside or outside blockchain networks to run transactions foster market stability through a negative influence on price volatility.

Table 4. Token dummies effect on tokens price volatility.

	Dependent Variable: Tokens Price Volatility				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Earning Potential	−0.00128	−0.00127	−0.00167	−0.00108	−0.00219
	(0.00296)	(0.00266)	(0.00253)	(0.00225)	(0.00246)
Right to vote	0.00273	0.00205	0.00246	0.00103	0.00254
	(0.00211)	(0.00196)	(0.00194)	(0.00186)	(0.00209)
Get access	0.00463	0.00270	0.00249	0.00243	0.00304
	(0.00286)	(0.00271)	(0.00265)	(0.00235)	(0.00273)
Get discount	−0.00830	−0.00649	−0.00699	−0.00730	−0.00728
	(0.00617)	(0.00634)	(0.00588)	(0.00591)	(0.00591)
Get reward	−0.00000479	−0.00172	−0.00181	−0.000438	−0.00118
	(0.00338)	(0.00326)	(0.00313)	(0.00302)	(0.00341)
Medium of exchange	−0.00274	−0.00364	−0.00444 **	−0.00411 **	−0.00413 **
	(0.00238)	(0.00225)	(0.00221)	(0.00201)	(0.00202)
Ethereum	0.00331	0.00373 *	0.00391 **	0.00374 **	0.00376 **
	(0.00242)	(0.00203)	(0.00181)	(0.00175)	(0.00168)
(log) Token price		−0.00177 ***	−0.00177 ***	−0.00176 ***	−0.00176 ***
		(0.000627)	(0.000596)	(0.000592)	(0.000592)
ROI			0.00111 ***	0.00111 ***	0.00110 ***
			(0.000129)	(0.000129)	(0.000127)
(log) Transfer count				−0.00034 ***	−0.00033 ***
				(0.00010)	(0.00011)
(log) Mean TX size					0.0003 **
					(0.00014)
Constant	0.0644 ***	0.0695 ***	0.0668 ***	0.0742 ***	0.0633 ***
	(0.00395)	(0.00384)	(0.00392)	(0.00432)	(0.00861)
N Observations	93,923	93,923	93,923	93,923	93,923
N Tokens	58	58	58	58	58
Time FE	✓	✓	✓	✓	✓
R^2	0.0533	0.0692	0.1828	0.1882	0.1943
Adjusted R^2	0.0531	0.0690	0.1826	0.1880	0.1941
F	22.24 ***	26.76 ***	76.92 ***	83.66 ***	88.70 ***

Note: All the variables refer to monthly time intervals. Clustered SE at the token level are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

In addition, the statistics at the bottom of Table 4 highlight the models' progressively increasing ability to explain the variation in tokens' price volatility. The F-statistic shows a clear upward trend across all five models, with statistically significant values at the 1% level in each model specification. The steady increase in the F-statistic, particularly in the later models, underscores the enhanced explanatory power as more control variables, such as token price and transfer count, are included.

Figure 4 displays the token dummy coefficients corresponding to the fifth column of the results in Table 4, along with their respective confidence intervals. The figure confirms that only the coefficients for being a medium of exchange and being part of the Ethereum blockchain are statistically significant, as their confidence intervals remain entirely on one side of the zero threshold, not crossing the vertical black dashed line. Moreover, Figure 4 illustrates that tokens functioning as a medium of exchange are negatively correlated with price volatility, while being part of the Ethereum ecosystem has a positive impact.

In summary, concerning the results obtained in the first step of the empirical analysis, we found evidence of how different characteristics of tokens affect the two main metrics considered in this paper (i.e., active address count and tokens price volatility). On the one hand, tokens that offer earnings potential and give access to voting rights within the blockchain ecosystem have a negative impact on the active user base, fostering token-holding strategies. On the other hand, belonging to the Ethereum ecosystem makes tokens more volatile in a statistically significant way. In addition, the results presented in Tables 3 and 4 show that, from a tokenomics perspective, there exists a negative link between active addresses and tokens price volatility that is driven by the usage of tokens as a medium of exchange. Indeed, while this tends to stimulate more activity within blockchain ecosystems, it can also stabilize demand for the tokens and decrease price volatility over time.

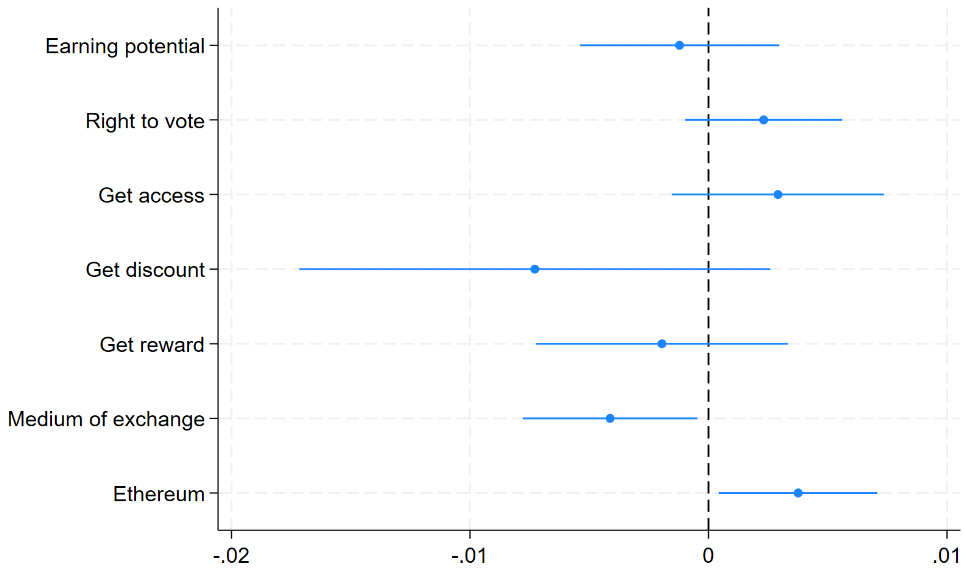

Figure 4. Token dummies effect on price volatility—coefficients chart.

The findings of this first analysis step are also relevant from a strategic point of view when designing blockchain-based projects that involve the implementation of a token. Depending on the nature of the project, one of the choices that need to be evaluated during the token design process relates to the intention to create an incentive system that influences user behavior regarding the duration of token holding, thereby decreasing the velocity and affecting tokens' value over time. From our findings, we can infer that allowing users to stake their tokens and earn a profit for holding them makes it possible to incentivize users to retain their tokens instead of frequently transacting them. Staking involves users locking up their tokens for a specified duration, contributing to the network's security and consensus mechanisms. In return, they receive rewards, usually in the form of additional tokens. This approach aligns with the goal of reducing token velocity by providing economic benefits to long-term holders. Based on our findings, another way to create an incentive to hold the tokens for more extended periods is to give users the right to influence the policy-making process of the blockchain ecosystem, allowing them to use the token to vote within the network. Indeed, by allowing token holders to use their digital assets for voting purposes rather than spending them, they obtain a tangible reason to retain and accumulate tokens. This approach empowers token holders, allowing them to have a say in important decisions, which can foster a sense of ownership and community participation.

On the other hand, when it comes to price volatility, our results suggest that tokenomics, apart from foreseeing the use of the token as a medium of exchange, does not play a significant role in its determination. This implies that it will be necessary to rely on other levers to influence this metric in the project design phase. Evidently, the first alternative for keeping volatility under control is to create a *stablecoin*, i.e., a token that has the precise objective of maintaining a certain price stability over time. Alternatively, the token might be pegged to the value of an underlying asset (e.g., precious metals). When the token price is not constrained by the performance of other markets or fixed at a certain level, the method to keep price volatility under control refers to levers that can be controlled at the token design stage, such as the supply strategy (along with the inflationary system). However, it is important to note that even with these design choices, the control over price volatility is limited. Since the volatility is considered exogenous in this case (as it is not reliant on other markets), the decisions made during token design can somewhat influence volatility. Still, they cannot provide full control over it.

In addition to the main empirical analysis, a series of robustness checks have been developed for the models estimated in the first step of the analysis. Considering the wide range of variation in the two main variables involved in the analysis (active address count and tokens price volatility) we use trimming and winsorizing methods to deal with potential outlier bias. In the trimming case, the method allows for the direct ignoring of outliers by removing a certain portion of observations from the tails of the variable distributions. Specifically, we implement the trimming method by shrinking the distributions between the 1st and 99th percentiles. Subsequently, we perform the same estimations using the modified sample in order to check whether the findings are consistent with the ones presented in Tables 3 and 4 without variations in the distributions. These results are presented in Appendix A within Tables A4 and A6. In particular, Table A4 refers to the trimming results where the dependent variable is the active address count, while Tables A6 is related to the trimming findings where the dependent variable is the tokens price volatility. The results of these robustness checks show how removing a certain percentage of lower and upper values of our two main metrics leads to consistent findings with respect to those obtained without changing variable distributions. The same logic is applied to perform the winsorizing method. However, in this case, winsorization limits extreme values in the distribution tails instead of excluding observations to reduce the potential bias caused by outliers. Therefore, we restrict values between the 1st and 99th percentiles, though not affecting the original sample size. The winsorization findings are presented in Appendix A within Tables A5 and A7. Specifically, Table A5 relates to winsorizing results where the dependent variable is the count of active addresses, while Table A7 shows the findings applying the winsorizing method where the dependent variable is the tokens price volatility. Also in this case, the robustness checks confirm the findings obtained in the main analysis, overall maintaining the same sign and statistical significance of the estimates shown in Tables 3 and 4.

In the second step of the analysis, we investigate how the volatility of token prices influences the active user base of blockchain networks. Table 5 shows the results of the fixed effects panel regressions. The structure of the table follows a stepwise approach as in the previous cases. Column 1 shows the results of the row model (where token price volatility is the only regressor), while Column 5 displays the estimates of the full control model. In addition, as in the previous cases, the standard errors in parentheses beneath estimates are clustered at the token level.

The first line of results refers to the estimates of the effect of token price volatility on the active address count. In all the specifications, the coefficients of token price volatility appear negative and statistically significant. We interpret a negative effect on the active address count as an incentive for users to hold their tokens, reducing their activity in the network. In the same way, the price volatility of tokens appears to be in a negative relationship with the active user base, providing evidence that higher price volatility in the blockchain-based token market may be perceived by users as an opportunity rather than a liability, taking advantage of potential appreciation windows, and tending to trade their tokens less when price volatility increases. Taking into consideration the coefficient estimate of price volatility in Column 5, evaluated at the average, it implies that a 10% increase in the price volatility causes a decrease of around 3616 active addresses, which corresponds to an average decrease of 5.88% in active addresses. The statistics at the bottom of Table 5 highlight, also in this case, the models' progressively increasing ability to explain the variation in the outcome variable. The F-statistic demonstrates a clear upward trend across all five models. This increase highlights the improved explanatory power as additional control variables, like token price and mean TX size, are incorporated.

Table 5. Tokens price volatility effect on active address count.

	Dependent Variable: **Active Address Count**				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
(log) Price volatility	−31,622.1 *	−37,720.7 **	−37,133.0 **	−39,270.8 **	−36,164.1 **
	(16,076.1)	(14,560.1)	(15,205.2)	(15,958.5)	(15,406.5)
(log) Token price		67,416.0 ***	67,423.0 ***	56,042.6 **	60,587.0 **
		(21,341.7)	(21,334.5)	(24,556.2)	(25,672.4)
ROI			−10.37	−10.28	−10.26
			(20.62)	(20.95)	(21.04)
(log) Transfer count				19,643.7	18,175.5
				(13,703.3)	(13,569.8)
(log) Mean TX size					−5210.8 *
					(3089.4)
N Observations	93,923	93,923	93,923	93,923	93,923
N Tokens	58	58	58	58	58
Token FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
R^2	0.0107	0.2441	0.2443	0.2706	0.2728
Adjusted R^2	0.0106	0.2440	0.2441	0.2704	0.2726
F	0.83	2.25 **	2.13 **	2.87 ***	3.29 ***

Note: All the specifications contain token FE and time FE. All variables refer to monthly time intervals. Clustered SE at the token level are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Figure 5 presents the price volatility coefficients reported in Table 5 across five models, corresponding to all results columns. The coefficients, accompanied by confidence intervals, help visualize the empirical results by showing how price volatility influences the dependent outcome—the active address count—across different model specifications. Notably, the confidence intervals of the coefficients do not overlap the zero threshold (in this case, horizontal) in every model, indicating that price volatility is always statistically significant in all the models.

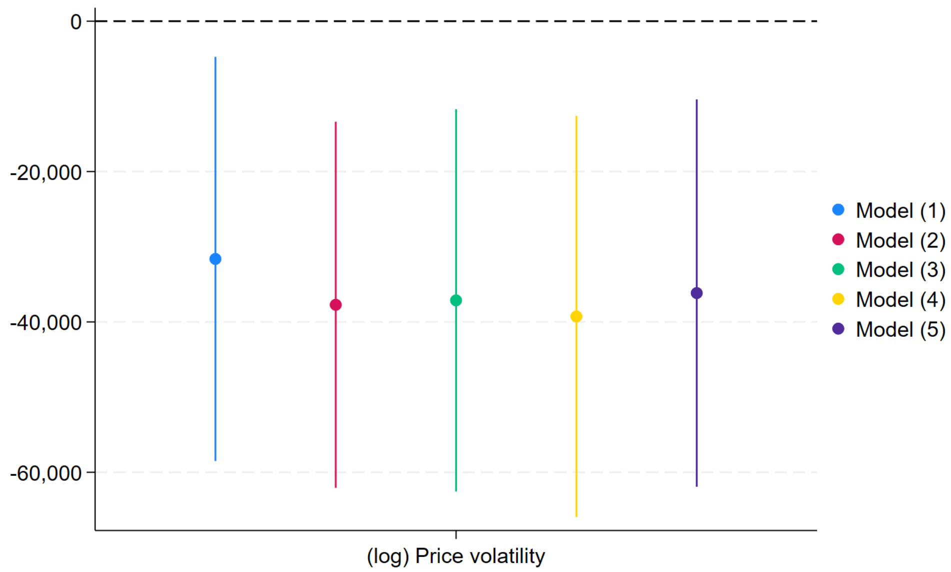

Figure 5. Price volatility effect on active address count—coefficients chart.

This result corroborates the hypothesis according to which token price volatility can act as a trigger to holding strategies reducing transactional activities instead of being necessarily detrimental to market conditions. As such, they demonstrate that price volatility, in the context of blockchain-based digital assets, may be perceived more as a feature than a problem, considering that other factors could play a role in this framework. For instance, network fees, lack of liquidity, or concerns about market manipulation can be regarded as other potentially influential factors. Yet, these findings must also be evaluated in relation to their context. Indeed, the valuation mechanism of these financial instruments is inherently different from that of traditional tools. Unlike the latter, blockchain-based tokens offer exponential windows of appreciation, given the critically different underlying basis. In the context of traditional financial tools, the market system appears closed, restricted to the timetables and geographies of conventional stock markets. On the contrary, digital asset markets exhibit openness to global exposure, with no mechanisms of forced closure or cool down, and are characterized by an ecosystem approach rather than an equity market attitude.

Also, in the case of the second step of empirical analysis, we have performed a series of robustness checks based on trimming and winsorizing methods to prove that the potential presence of outliers in the dataset does not threaten the validity of the results. Firstly, we implement the trimming method by shrinking the distribution of the active address count between the 1st and 99th percentiles. We perform the same estimations using the modified samples in order to check whether the findings are consistent with the ones presented in Table 5. These results are presented in Appendix A within Table A8. The estimates of this robustness check show how shrinking the distribution of the active address count leads to consistent findings with respect to those obtained without removing a certain percentage of lower and upper values from the variable distribution. The same logic is then applied to perform the winsorizing method. Therefore, we restrict values between the 1st and 99th percentiles of the active address count, not affecting the original sample size. The winsorization findings related to the second step of the analysis are presented in Appendix A within Table A9. Also in this case, the robustness check confirms the findings obtained in the main analysis, maintaining the same sign and statistical significance of the estimates shown in Table 5.

As discussed in Section 5, we conduct the same analysis related to the relationship between the active address count and the token price volatility to further investigate this phenomenon by implementing an FGLS estimator. In particular, FGLS offers more efficient estimators than OLS in the case of heteroskedasticity and autocorrelation but requires a balanced dataset. Therefore, we estimate the model presented in Equation (3) using a balanced subsample of 30,200 observations for 40 blockchain-based tokens between 31 December 2020 and 24 January 2023. Table 6 shows the results of this analysis. The structure of the table remains coherent with respect to the previous one. Hence, in the first line of findings, we can observe the estimates related to the impact of token price volatility on the count of active addresses in the networks. We find negative and statistically significant estimates in all five model specifications.

Therefore, we can observe that even when applying the FGLS estimator to handle potential autocorrelation of the variables involved, the findings remain consistent with those obtained by implementing an FE model. In terms of magnitude, the coefficient estimate of tokens price volatility in Column 5, evaluated at the average of the balanced subsample utilized in Table 6, implies that a 10% increase in the price volatility causes a decrease of around 3.96% in the monthly active addresses (i.e., about 3,172 less active addresses on a monthly basis). Note that the difference in the magnitude of the negative impacts of token price volatility on the active address count between FE (Table 5) and FGLS (Table 6) estimators can be attributed to two main factors. Firstly, this difference could be generated by the diversities between the samples used in the two estimations. Secondly, there could be an autocorrelation bias that the FE model is not able to handle even when implementing clustered standard errors. Nevertheless, the findings of the two tables are consistent with each other. Therefore, we can conclude that taking into consideration all the main potential identification threats, when the token price volatility rises by 10%, the active address count diminishes in a range between 3.96% and 5.88%.

Table 6. Tokens price volatility effect on active address count—FGLS estimator.

	Dependent Variable: Active Address Count				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
(log) Price volatility	−22362.8 ***	−22,254.1 ***	−24,878.3 ***	−29,835.1 ***	−31,728.3 ***
	(1686.7)	(1493.2)	(1656.0)	(1362.3)	(1393.5)
(log) Token price		4721.8 ***	4375.2 ***	4920.5 ***	4637.2 ***
		(329.4)	(335.6)	(217.0)	(221.4)
ROI			58.27 ***	3.848	3.673
			(10.04)	(9.469)	(9.545)
(log) Transfer count				16,541.1 ***	17,079.3 ***
				(287.3)	(300.4)
(log) Mean TX size					1561.4 ***
					(266.0)
Constant	−45,183.9 ***	−53,394.5 ***	−61,580.6 ***	−208,143.4 ***	−231,612.4 ***
	(5220.7)	(4624.3)	(5175.7)	(5150.9)	(6457.3)
N Observations	30,200	30,200	30,200	30,200	30,200
N Tokens	40	40	40	40	40
Time FE	✓	✓	✓	✓	✓
Wald Chi^2	186.83	444.93	417.82	3925.17	3991.67
Prob > χ^2	0.000	0.000	0.000	0.000	0.000

Note: All the variables refer to monthly time intervals. Clustered SE at the token level are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

The results presented in Section 5 about panel unit root tests, providing strong evidence of stationarity for all variables in our analysis, also apply in relation to the estimates of Tables 5 and 6. In particular, they confirm that our models do not need the application of a de-trending approach. Therefore, the large coefficients observed in Tables 5 and 6 capture the true relationship between token price volatility and the active user base without being influenced by non-stationarity issues.

In addition, Figure 6 illustrates the price volatility coefficients reported in Table 6 across five models, corresponding to all the results columns. The coefficients, along with their confidence intervals, visually represent the empirical findings, demonstrating how price volatility affects the dependent variable—the active address count—across different model specifications using the FGLS estimator. Importantly, also in this case, the confidence intervals do not intersect the zero threshold in all the models, indicating that price volatility is statistically significant throughout.

The results reported in Table 6 and Figure 6 further confirm our hypothesis, according to which the characteristics of the traditional financial market and the blockchain-based digital asset market, as well as the investors acting in them, show substantial divergences. Indeed, outlining the differences between traditional and digital markets also provides insight into the divergence between users of these two systems and their attitudes toward investment. The theory related to behavioral finance, based on traditional financial assets, tends to distinguish gamblers from standard retail investors in their investment decision-making strategies and attitude with respect to risk. Specifically, retail investors tend to have a longer-term perspective and a preference for lower risk in conjunction with a greater likelihood of positive expected returns and greater economic utility (Arthur et al. 2016). However, economic theory has always associated risk with higher variability in the value of portfolios (Engle 2004).

Consequently, in traditional financial markets, the evidence shows how gamblers, leading the market's action, not only produce volatility but also a non-negligible share of them are attracted by the increase in volatility itself (Clark et al. 2018). The empirical evidence in this paper might suggest how blockchain technology changes traditional rules, overturning roles. In the context of digital assets, price volatility gives access to investment strategies over extended time horizons, stimulating token retention and not just speculation-related trading activities. From this perspective, Bonaparte (2022) discusses the relationship between household time horizon and blockchain token ownership, empirically showing how households with longer time horizons are more likely to own tokens in their portfolios. The article also presents a theoretical life cycle model to explain this relationship that, in contrast with the empirical results, suggests that cryptocurrency owners have a short time horizon. When considered collectively, the author interprets the opposing empirical findings and theoretical model inference as an indication that individuals with a blockchain token investment perceive it as a pseudo-productive/long-term asset class, as opposed to regarding tokens merely as speculative assets. In addition, Liebi (2022) examines if blockchain fundamentals, such as the active addresses-to-network value ratio, determine token prices. The results suggest the presence of a significant connection between token prices and blockchain fundamentals, challenging the view of long-run speculations in digital asset markets.

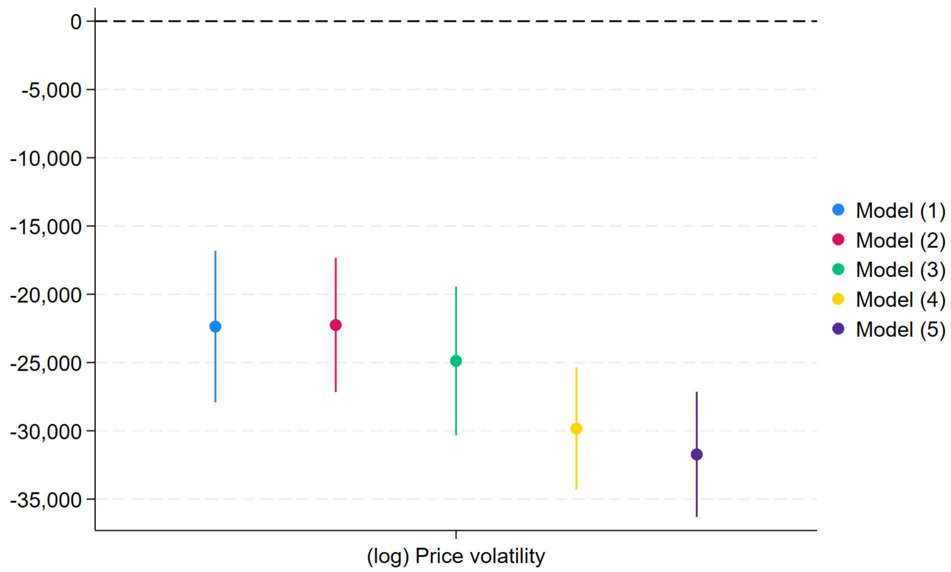

Figure 6. Price volatility effect on active address count—FGLS estimator—coefficients chart.

7. Conclusions

The ability of blockchain-based tokens to represent almost any type of asset in digital form, as well as to create new use cases and business opportunities, highlights their considerable potential. Regardless of the specific functionalities of tokens, their price increase, elevated transparency, absence of intermediaries, and high liquidity linked to reduced costs regarding price discovery and market fragmentation make them a new and appealing asset class. Indeed, digital assets inherently diverge from standard financial instruments with respect to economic factors such as investment returns and volatility spillovers (Bianchi 2020) as well as dividends generation (Prat et al. 2024).

Considering the wide variety of tokens in circulation and the functionalities they can perform, we conduct a two-step analysis in this paper to investigate the relationship between token price volatility and active addresses. We first examine the tokenomics drivers of token price volatility and active addresses. We do so by implementing two pooled OLS models, where active address count and price volatility are the dependent variables, and our main regressors are the token features deriving from the tokens classification analysis discussed in Section 3. Our results suggest that active addresses and price volatility are both driven by the usage of tokens as a medium of exchange with a positive correlation for the former and a negative one for the latter. This is extremely important as it shows how token usage dynamics can impact user engagement and market stability. Moreover, we also show that when tokens offer earning potentials and voting rights to token holders, they tend to have lower activity levels within the network. This is reflected in the reduced number of transactional activities. Instead, in the case of price volatility, only Ethereum-based tokens show higher levels of volatility. One potential explanation for this finding is rooted in the comparative youthfulness of Ethereum-based projects, which are generally more recent on average than other digital assets in the dataset. Less mature projects are commonly linked to diminished external propagation, leading to heightened transaction sensitivity in their market value compared to their more established counterparts.

Subsequently, we investigate the relationship between token price volatility and the activity of the user base, highlighting the distinctions between traditional and digital asset markets, and also offering a perspective on the disparities among users of these systems and their varying investment attitudes. Our findings show that, on average, an increase of 10% in the price volatility of tokens is associated with a decrease in the activity of the blockchain networks in a range between 3.96% (considering FGLS estimates) and 5.88% (considering FE estimates). This result supports our hypothesis that volatility may not be perceived negatively by users in the framework of blockchain tokens, acknowledging other potentially influential factors such as network fees, lack of liquidity, or concerns about market manipulation. Price fluctuations can signal a healthy and active market exposed to world-scale influences without forced stop periods. Therefore, beyond speculative practices, the volatile nature associated with digital assets can trigger token-holding strategies for extended investment time horizons (Bonaparte 2022). In addition, a reduction in the user base's activity due to higher price volatility might produce network effects linked to specific token features that may attract growing numbers of users favoring tokens to enhance their values.

This paper presents some limitations and inspiration for future research. First, the analysis assumes that control variables added in the empirical models are sufficient to capture the external aspects influencing token price volatility and user engagement other than token features. However, unobserved factors, such as external market shocks, regulatory changes, or broader macroeconomic trends, may also influence these relationships. Additionally, the use of aggregated monthly data may overlook short-term fluctuations or dynamic shifts that occur within shorter time frames. Future research could contribute to this by utilizing higher-frequency data to capture real-time token behavior and assess the impact of external factors like market sentiment or technological advancements on blockchain networks. Moreover, expanding the analysis to explore how different governance structures or token incentive mechanisms impact both price volatility and user activity could offer additional insights. Comparative studies across various blockchain ecosystems might also shed light on cross-platform behavior and market dynamics, contributing to a more comprehensive understanding of the factors shaping digital asset markets.

Author Contributions: R.M.: conceptualization, methodology, software, data curation, writing—original draft, visualization, formal analysis, investigation. E.F.: writing—review and editing. M.F.: conceptualization, methodology, writing—review and editing, supervision. F.M.: writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data supporting this study are publicly available at https://coinmetrics.io (Accessed on 25 January 2023).

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Supplementary Analysis and Robustness Checks

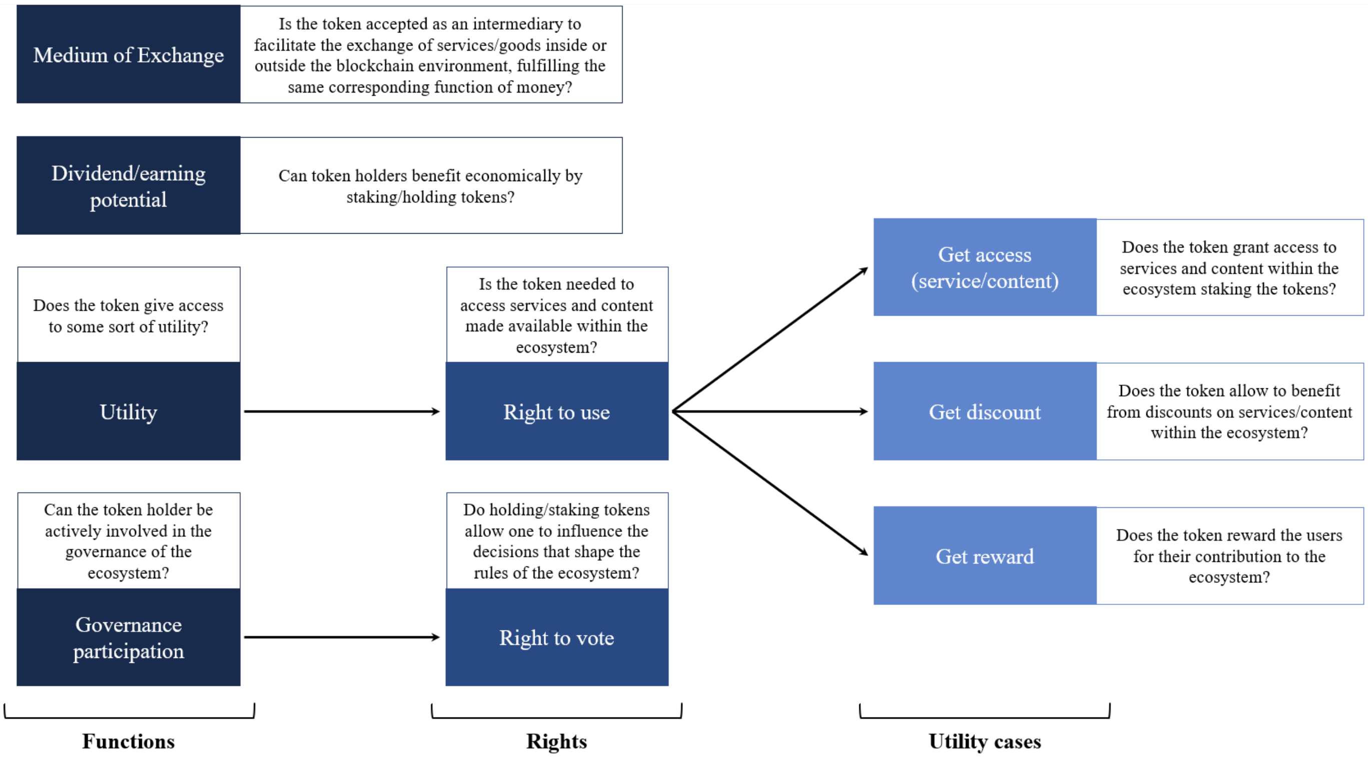

Figure A1. Token features classification process.

TECHNOLOGY				BEHAVIOR						COORDINATION			
Chain	**Permission**	**Number of Blockchains**	**Representation Type**	**Burnability**	**Expirability**	**Spendability**	**Fungibility**	**Divisibility**	**Tradability**	**Underlying Value**	**Supply Strategy**	**Incentive Enablers**	**Incentive Drivers**
New Chain, new code	Permissioned	Single Chain	Common	Burnable	Expirable	Spendable	Fungible	Fractional	Tradable	Asset-based	Schedule-based	Right to work	Get access (to content/service)
New Chain, forked code	Permissionless	Cross Chain	Unique	Non-Burnable	Non-Expirable	Non-Spendable	Non-Fungible	Whole	Non-Tradable	Network Value	Pre-mined scheduled distribution	Right to use	Get discount
Forked Chain, forked Code							Hybrid	Singleton	Delegable	Share-like	Pre-mined one-off distribution	Right to vote	Get revenue (increase existing business)
Issued on top of a protocol											Discretionary	Unit of account	Get reward (new economy creation)
											Matching demand	Medium of exchange	Dividend/Earning Potential (for holding or staking)
												Store of value	Appreciation potential (Speculation)
													Participate in governance
													Gain reputation

Figure A2. Morphological token classification framework. Source: Freni et al. (2022).

Table A1. Dataset structure composition.

#	Token	N Obs	Date of Birth	Blockchain	Medium of Exchange	Get Access	Get Discount	Get Reward	Earning Potential	Right to Vote
1	1INCH	730	Dec 2020	Ethereum					✓	✓
2	AAVE	807	Jan 2020	Ethereum		✓	✓		✓	✓
3	ADA	1,851	Sep 2017	Cardano	✓				✓	
4	ALGO	1,283	Jun 2019	Algorand	✓	✓		✓		✓
5	ALPHA	786	Oct 2018	Ethereum	✓			✓		✓
6	ANT	1720	May 2017	Ethereum		✓				✓
7	BAL	914	Jun 2020	Ethereum					✓	✓
8	BAT	1907	May 2017	Ethereum	✓			✓		
9	BCH	1973	Aug 2017	Bitcoin Cash	✓					
10	BNB	617	Jul 2017	Binance Chain	✓	✓	✓		✓	
11	BSV	1306	Nov 2018	Bitcoin SV	✓					
12	BTC	4544	Jan 2009	Bitcoin	✓					
13	BTG	1870	Nov 2017	Bitcoin Gold	✓					
14	CRO	1377	Nov 2018	Cronos Chain		✓	✓		✓	
15	CRV	863	Aug 2020	Ethereum		✓		✓	✓	✓
16	CVC	1932	Jul 2017	Ethereum		✓				
17	DASH	3243	Jan 2014	Dash					✓	
18	DGB	2876	Jan 2014	DigiByte	✓	✓		✓		
19	DOGE	3259	Dec 2013	Dogecoin	✓	✓		✓		
20	DOT	623	May 2020	Polkadot					✓	✓
21	DRGN	1818	Aug 2017	Dragochain		✓				
22	ELF	1780	Dec 2017	Aelf	✓					✓
23	EOS	1661	Jun 2018	Eos.io		✓			✓	
24	ETC	2345	Jul 2016	Ethereum Classic	✓					
25	ETH	2697	Jul 2015	Ethereum	✓					
26	GNO	2064	Apr 2017	Gnosis Chain					✓	✓
27	GNT	1928	Nov 2016	Golem Network	✓				✓	✓
28	HEDG	482	Apr 2019	Ethereum	✓			✓		
29	HT	1391	Jan 2018	Ethereum	✓	✓	✓	✓		✓
30	ICP	594	May 2021	Internet Computer		✓		✓		✓
31	KNC	1916	Feb 2018	Ethereum					✓	✓
32	LINK	1914	Sep 2017	Chainlink		✓		✓		
33	LOOM	1354	Oct 2017	Ethereum	✓	✓			✓	
34	LPT	1432	May 2018	Ethereum	✓	✓			✓	
35	MATIC	1339	Apr 2019	Ethereum	✓				✓	✓
36	MKR	1826	Dec 2019	Ethereum					✓	✓
37	NEO	1990	Oct 2016	Neo	✓				✓	✓
38	NXM	822	May 2019	Ethereum	✓	✓	✓	✓		✓
39	OMG	1990	Jul 2017	Ethereum					✓	
40	PAY	1604	Jun 2017	TenX	✓					
41	PERP	690	Sep 2020	Ethereum					✓	✓
42	REV	792	Sep 2017	Ethereum		✓		✓		
43	SNX	991	Sep 2017	Ethereum	✓	✓			✓	
44	SRM	867	Aug 2020	Solana			✓	✓	✓	✓
45	SUSHI	846	Aug 2020	Ethereum					✓	✓
46	SWRV	595	Sep 2020	Ethereum						✓
47	TRX	1645	Jun 2018	Tron	✓					
48	UMA	839	Dec 2019	Ethereum					✓	✓
49	UNI	829	Nov 2018	Ethereum					✓	✓
50	VTC	3253	Jan 2014	Vetcoin	✓					
51	WTC	1363	Aug 2017	Waltonchain	✓					
52	XEM	2826	Mar 2015	NEM	✓	✓				✓
53	XLM	2611	Jul 2014	Stellar	✓					
54	XTZ	1370	Jun 2018	Tezos	✓				✓	✓
55	XVG	1883	Oct 2014	Verge	✓					
56	YFI	884	Jul 2020	Ethereum		✓			✓	✓
57	ZEC	2249	Oct 2016	Zcash	✓					
58	ZRX	1962	Jul 2017	Ethereum	✓					✓
	Total	93,923			33	21	6	13	27	28

Table A2. Fisher-type tests table—inverse chi-squared statistic.

Variable	Lags	Inverse Chi-Squared	*p*-Value
Active addresses	1	184.7192	0.0001
	2	168.1469	0.0011
	3	213.6843	0.0000
	4	217.2419	0.0000
Price volatility	1	1310.3928	0.0000
	2	1301.6971	0.0000
	3	1338.5814	0.0000
	4	1307.3500	0.0000
(log) Token price, USD	1	210.9566	0.0000
	2	179.5708	0.0001
	3	166.2093	0.0016
	4	159.7928	0.0044
ROI	1	2119.7354	0.0000
	2	2051.1333	0.0000
	3	2072.6034	0.0000
	4	1960.8145	0.0000
Transfers count	1	198.6007	0.0000
	2	154.4287	0.0099
	3	150.9279	0.0162
	4	168.1015	0.0011
Avg TX size, USD	1	906.8036	0.0000
	2	690.3094	0.0000
	3	543.9986	0.0000
	4	526.4545	0.0000

Table A3. Cross-correlation table.

Variables	Price Volatility	Token Price	ROI	Transfer Count	Mean TX Size	Ethereum	Medium of Exchange	Earning Potential	Get Access	Get Discount	Get Reward	Right to Vote
Price volatility	1.000											
Token price	-0.092	1.000										
ROI	0.342	−0.028	1.000									
Transfer count	−0.045	0.025	0.007	1.000								
Mean TX size	0.011	−0.016	−0.011	−0.003	1.000							
Ethereum	0.070	0.125	−0.019	−0.063	−0.020	1.000						
Medium of exchange	−0.031	−0.307	0.041	0.070	0.023	−0.187	1.000					
Earning potential	0.010	0.205	−0.007	0.078	−0.019	0.278	−0.304	1.000				
Obtain access	0.039	−0.284	0.013	0.099	0.039	0.123	0.069	−0.038	1.000			
Obtain discount	−0.033	0.053	0.010	−0.025	−0.006	0.086	−0.051	0.138	0.301	1.000		
Obtain reward	0.021	−0.304	0.006	−0.036	−0.013	0.040	0.136	−0.271	0.481	0.220	1.000	
Right to vote	0.051	0.095	−0.026	−0.067	0.035	0.336	−0.188	0.323	0.010	0.154	−0.003	1.000

Table A4. Robustness check—token dummies effect on active addresses. Trimming (1-99).

	Dependent Variable: Active Address Count				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Earning Potential	−49,987.2 *	−51,168.0 **	−51,063.6 **	−60,526.1 ***	−64,988.1 ***
	(27,264.8)	(20,589.3)	(20,556.4)	(20,759.3)	(22792.6)
Right to vote	−55,219.1 **	−43,026.5 ***	−43,149.0 ***	−42,662.3 ***	−42,719.8 ***
	(23,651.9)	(15,383.8)	(15,420.1)	(15,385.3)	(15,417.3)
Get access	−49,813.5 *	−15,043.1	−14,987.1	−15,172.0	−12,685.8
	(25,461.0)	(18,668.4)	(18,650.3)	(16,642.5)	(15,960.1)
Get discount	21,692.9	−8647.3	−8481.5	27,135.4	19,448.3
	(19,656.8)	(32,271.4)	(32,209.5)	(29,493.4)	(28,318.8)
Get reward	−34,662.7	−3688.2	−3661.4	−2985.2	−2930.4
	(28,345.1)	(17,386.3)	(17,382.8)	(17,588.4)	(17,612.3)
Medium of exchange	26,472.0 *	43,624.7 **	43,859.6 **	42,514.8 **	42,489.7 **
	(14,124.2)	(16,976.0)	(17,046.0)	(16,929.0)	(16,928.7)
Ethereum	13,664.6	5811.4	5768.2	32735.5 *	27,882.1
	(33,654.9)	(21,962.8)	(21,982.8)	(18,931.2)	(20,597.1)
(log) Token price		32,365.8 **	32,365.6 **	22,938.5 *	21,072.4 *
		(14,139.8)	(14,130.9)	(13,451.4)	(12,199.6)
ROI			−32.08 *	−33.54 *	−36.66 *
			(17.63)	(17.64)	(18.89)
(log) Transfer count				17,311.3 ***	18,613.4 ***
				(3643.3)	(3837.1)
(log) Mean TX size					5691.9
					(4225.2)
Constant	86,975.1 **	−3750.6	−2957.8	12,2652.3 ***	16,8126.1 ***
	(37900.9)	(27,592.6)	(27,459.8)	(35,846.7)	(57,566.1)
N Observations	92,040	92,040	92,040	92,040	92,040
N Tokens	58	58	58	58	58
Time FE	✓	✓	✓	✓	✓
R^2	0.1340	0.3962	0.3967	0.4660	0.4714
Adjusted R^2	0.1338	0.3961	0.3966	0.4659	0.4713
F	2.54 ***	2.28 ***	2.54 ***	4.45 ***	4.51 ***

Note: All the variables refer to monthly time intervals. Clustered SE at the token level are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A5. Robustness check—token dummies effect on active addresses. Winsorizing (1-99).

	Dependent Variable: Active Address Count				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Earning Potential	−60,894.1 *	−61,003.5 **	−60,857.7 **	−73,414.7 ***	−78,085.0 ***
	(30,667.7)	(23,293.5)	(23,245.0)	(25,496.4)	(27,632.3)
Right to vote	−62,836.7 **	−49,994.6 ***	−50,145.3 ***	−49,362.4 ***	−49,406.0 ***
	(25,839.8)	(17,473.4)	(17,515.1)	(17,351.0)	(17,368.6)
Get access	−59,624.5 **	−22,747.7	−22,671.0	−21,423.5	−18,867.5
	(28,691.2)	(22,631.2)	(22,598.1)	(20,335.1)	(19,928.9)
Get discount	28,355.0	−6246.5	−6062.2	41,771.8	34,447.5
	(22,358.4)	(34,006.4)	(33,934.7)	(36,223.4)	(36,486.5)
Get reward	−44,564.9	−11,831.9	−11,798.4	−10,719.2	−10,678.0
	(31,711.1)	(21,664.3)	(21,648.3)	(21,655.5)	(21,692.5)
Medium of exchange	29,529.5 *	46,808.2 **	47,101.9 **	44,990.4 **	44,971.1 **
	(15,001.2)	(17,615.4)	(17,688.0)	(17,516.9)	(17,517.6)
Ethereum	8000.8	−21.55	−90.22	1007.0	1026.4
	(32,513.4)	(21,320.2)	(21,348.4)	(21,242.5)	(21,251.9)
(log) Token price		33,668.4 **	33,670.6 **	33,579.9 **	33,581.1 **
		(15,872.2)	(15,861.5)	(15,840.7)	(15,841.1)
ROI			−40.95 **	−43.84 **	−47.09 **
			(19.89)	(20.21)	(21.49)
(log) Transfer count				22,357.3 ***	23,652.3 ***
				(7522.2)	(7495.7)
(log) Mean TX size					5744.9
					(4993.7)
Constant	110,127.6 **	14,260.0	15,236.1	141,475.0 ***	187,116.5 ***
	(47,919.9)	(39,308.9)	(39,329.4)	(45,729.3)	(66,114.0)
N Observations	93,923	93,923	93,923	93,923	93,923
N Tokens	58	58	58	58	58
Time FE	✓	✓	✓	✓	✓
R^2	0.1391	0.3516	0.3522	0.4414	0.4454
Adjusted R^2	0.1389	0.3515	0.3520	0.4413	0.4453
F	1.25	1.90 **	2.02 **	3.09 ***	3.18 ***

Note: All the variables refer to monthly time intervals. Clustered SE at the token level are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A6. Robustness check—token dummies effect on price volatility. Trimming (1-99).

	Dependent Variable: **Tokens Price Volatility**				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Earning Potential	−0.000954	−0.000925	−0.00125	−.000817	−0.000805
	(0.00257)	(0.00235)	(0.00233)	(0.00229)	(0.00229)
Right to vote	0.00294	0.00242	0.00232	0.00221	0.00218
	(0.00186)	(0.00176)	(0.00184)	(0.00185)	(0.00187)
Get access	0.00422 *	0.00269	0.00257	0.00301	0.00297
	(0.00247)	(0.00235)	(0.00239)	(0.00239)	(0.00240)
Get discount	−0.00794	−0.00650	−0.00653	−0.00684	−0.00682
	(0.00498)	(0.00521)	(0.00513)	(0.00515)	(0.00515)
Get reward	−0.000573	−0.00191	−0.00206	−0.00222	−0.00219
	(0.00286)	(0.00285)	(0.00286)	(0.00288)	(0.00289)
Medium of exchange	−0.00215	−0.00290	−0.00451 **	−0.00443 **	−0.00431 **
	(0.00225)	(0.00213)	(0.00213)	(0.00210)	(0.00210)
Ethereum	0.00314	0.00349 *	0.00347 *	0.00330 *	0.00332 *
	(0.00212)	(0.00177)	(0.00181)	(0.00179)	(0.00179)
(log) Token price		−0.00142 **	−0.00154 ***	−0.00153 ***	−0.00153 ***
		(0.000564)	(0.000540)	(0.000536)	(0.000536)
ROI			0.0130 ***	0.0130 ***	0.0130 ***
			(0.000748)	(0.000748)	(0.000748)
(log) Transfer count				−0.0322 ***	−0.0322 ***
				(0.0088)	(0.0088)
(log) Mean TX size					0.0033 **
					(0.0013)
Constant	0.0626 ***	0.0667 ***	0.0644 ***	0.0642 ***	0.0642 ***
	(0.00340)	(0.00346)	(0.00357)	(0.00353)	(0.00353)
N Observations	92,044	92,044	92,044	92,044	92,044
N Tokens	58	58	58	58	58
Time FE	✓	✓	✓	✓	✓
R^2	0.0606	0.0738	0.1431	0.1448	0.1449
Adjusted R^2	0.0604	0.0737	0.1429	0.1446	0.1447
F	17.54 ***	29.44 ***	88.30 ***	92.87 ***	95.69 ***

Note: All the variables refer to monthly time intervals. Clustered SE at the token level are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A7. Robustness check—token dummies effect on price volatility. Winsorizing (1-99).

	Dependent variable: Tokens price volatility				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Earning Potential	−0.00119	−0.00119	−0.00150	−0.00106	−0.00105
	(0.00287)	(0.00258)	(0.00247)	(0.00243)	(0.00244)
Right to vote	0.00294	0.00230	0.00263	0.00251	0.00248
	(0.00204)	(0.00189)	(0.00188)	(0.00190)	(0.00191)
Get access	0.00466 *	0.00282	0.00265	0.00311	0.00308
	(0.00276)	(0.00259)	(0.00255)	(0.00254)	(0.00256)
Get discount	−0.00817	−0.00644	−0.00685	−0.00716	−0.00715
	(0.00595)	(0.00613)	(0.00575)	(0.00577)	(0.00577)
Get reward	−0.000543	−0.00218	−0.00225	−0.00242	−0.00239
	(0.00325)	(0.00314)	(0.00303)	(0.00305)	(0.00306)
Medium of exchange	−0.00268	−0.00355	−0.00419 *	−0.00386 *	−0.00387 *
	(0.00234)	(0.00222)	(0.00219)	(0.00216)	(0.00216)
Ethereum	0.00333	0.00373 **	0.00388 **	0.00371 **	0.00372 **
	(0.00234)	(0.00186)	(0.00184)	(0.00181)	(0.00182)
(log) Token price		−0.00168 ***	−0.00169 ***	−0.00167 ***	−0.00167 ***
		(0.000613)	(0.000588)	(0.000584)	(0.000584)
ROI			0.00894 ***	0.00893 ***	0.00893 ***
			(0.00129)	(0.00129)	(0.00129)
(log) Transfers count				−0.0034 ***	−0.0034 ***
				(0.00010)	(0.00010)
(log) Mean TX size					0.00028 **
					(0.00014)
Constant	0.0639 ***	0.0687 ***	0.0665 ***	0.0663 ***	0.0663 ***
	(0.00380)	(0.00371)	(0.00380)	(0.00376)	(0.00376)
N Observations	93,923	93,923	93,923	93,923	93,923
N Tokens	58	58	58	58	58
Time FE	✓	✓	✓	✓	✓
R^2	0.0576	0.0738	0.1564	0.1581	0.1583
Adjusted R^2	0.0574	0.0736	0.1563	0.1579	0.1581
F	21.27 ***	27.95 ***	66.44 ***	73.71 ***	75.59 ***

Note: All the variables refer to monthly time intervals. Clustered SE at the token level are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A8. Robustness check—price volatility effect on active addresses. Trimming (1-99).

	Dependent Variable: Active Address Count				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
(log) Price volatility	−18,279.5 *	−23,648.6 ***	−22,445.9 ***	−23,618.0 ***	−21,827.8 ***
	(10,590.2)	(6703.4)	(6250.5)	(5879.6)	(5213.8)
(log) Token price		61,171.5 ***	61,187.8 ***	55,350.1 **	58,075.7 **
		(20,092.4)	(20,074.0)	(21,598.7)	(22,723.4)
ROI			-20.70	-20.27	-20.24
			(13.97)	(14.36)	(14.49)
(log) Transfer count				9852.7 **	8964.1 *
				(4546.0)	(4823.9)
(log) Mean TX size					-3066.3
					(2214.1)
N Observations	92,040	92,040	92,040	92,040	92,040
N Tokens	58	58	58	58	58
Token FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
R^2	0.0079	0.3964	0.3969	0.4104	0.4121
Adjusted R^2	0.0077	0.3963	0.3968	0.4103	0.4120
F	1.97 **	2.30 **	2.37 **	4.43 ***	4.64 ***

Note: All the specifications contain token FE and time FE. All variables refer to monthly time intervals. Clustered SE at the token level are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A9. Robustness check—price volatility effect on active addresses. Winsorizing (1-99).

	Dependent Variable: Active Address Count				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
(log) Price volatility	−23,315.6 **	−29,253.3 ***	−28,201.9 ***	−29,719.6 ***	−27,395.5 ***
	(10,477.5)	(7539.5)	(7457.4)	(7495.4)	(7308.7)
(log) Token price		65,636.9 ***	65,649.4 ***	57,570.2 **	60,969.8 **
		(20,885.5)	(208,68.0)	(23,029.3)	(24,282.4)
ROI			−18.55	−18.48	−18.47
			(15.71)	(16.19)	(16.33)
(log) Transfer count				13945.6 *	12,847.2
				(8155.2)	(8356.0)
(log) Mean TX size					-3898.1
					(2512.1)
N Observations	93,923	93,923	93,923	93,923	93,923
N Tokens	58	58	58	58	58
Token FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
R^2	0.0094	0.3617	0.3620	0.3832	0.3852
Adjusted R^2	0.0093	0.3616	0.3619	0.3831	0.3851
F	1.30	2.41 **	2.30 **	2.68 ***	2.85 ***

Note: All the specifications contain token FE and time FE. All variables refer to monthly time intervals. Clustered SE at the token level are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Notes

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