The Dark Side of Decentralized Finance: Evidence from Meme Tokens

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Abstract

Technological innovations in decentralized finance have reduced the cost of listing and trading cryptocurrencies, resulting in a proliferation of meme tokens. Using novel blockchain data, we document issuance of more than 300,000 meme tokens in 2021, with total trading volume of more than $30 billion. Words related to animals (e.g. Doge), cartoons (e.g. Spongebob), and celebrities (e.g. Elon Musk) have been featured in token names. Exploiting the rich heterogeneity of such keywords, we find that investors' interests shift between distinct meme styles, which we define as tokens sharing the same meme keywords. Token issuers cater to investor demand by issuing more tokens with popular meme keywords and profit from such issuances, primarily through exit scams (e.g. "rug pulls"). Consistent with salience theory's prediction for competitive markets, issuers compete for investor attention by issuing tokens that feature more meme keywords and lower prices. In response to Elon Musk's tweets on DogeCoin, tokens whose names include "Doge" saw an increase in volumes, prices, and issuances relative to other non-Doge meme tokens. Our findings highlight the social aspects of meme-token investing. We also discuss how our findings are related to meme stocks.

Keywords: meme tokens, competition for attention, salience, fraud, investor protection

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1. Introduction

In early 2021, a group of investors, through Reddit and other social media platforms, started promoting GameStop, the world's largest video game retailer. The best-known social media where retail investors communicated was a subreddit called WallStreetBets. Elon Musk tweeted on January 26 with a single word "Gamestonk!!" along with a link to WallStreetBets. Pedersen (2022) documented that the GameStop stock experienced a dramatic increase in price, volume, and volatility, together with heightened investor attention to GameStop.

This paper studies the meme investment phenomenon in the crypto market. Meme is a newly coined word that is broadly defined as "an amusing or interesting item (such as a captioned picture or video) or genre of items that is spread widely online, especially through social media" (Merriam-Webster, 2022).[1] Meme tokens predate meme stocks. One example is DogeCoin, created in 2013 by two IBM engineers for fun (Kay, 2021). It used the doge meme, a funny image of a Shiba Inu that went viral on the internet. Around the time of the GameStop event, meme cryptos became popular. The price of DogeCoin increased from 0.3 cents in late 2020 to more than 60 cents in May 2021. Around the same time, many other meme tokens were issued to the market.

In this paper, we study meme tokens issued on the Binance Smart Chain from September 12, 2020 to December 31, 2021. Most meme tokens have humorous keywords, such as doge, floki, shiba, baby, and moon. We identify more than 500 such keywords and an enormous 311,354 meme tokens with such keywords. In 2021 alone, their trading volume was more than $30 billion, comparable to the total trading volume of GameStop in the same period.

[1] See https://www.merriam-webster.com/dictionary/meme

Relative to meme stocks, meme tokens provide several advantages for investigating the meme phenomenon. First, by design, meme tokens do not have any real business or utility (other than meme). In fact, many tokens are created based on almost identical source codes. They do not pretend to have real business or utility either, as indicated by the meme keywords in their token names. In contrast, meme stocks have fundamentals and their price changes may be driven by changing fundamentals.[2] Second, as discussed above, we have many more meme tokens with much richer heterogeneities, allowing us to conduct a granular analysis of the meme phenomenon with great statistical power. We document several stylized facts about this puzzling phenomenon.

We first entertain the possibility that investors may exhibit time-varying sentiments toward different types of tokens. A natural way of classifying tokens is based on meme keywords. Our data confirm this conjecture. We group tokens into 557 styles if they share the same meme keywords. We find that the returns of tokens within the same style are more strongly correlated than with other meme tokens. Different styles have remarkably different return patterns, indicating that investor sentiment switches between different styles.

On Binance Smart Chain, issuing and listing a new token to a decentralized exchange is low cost. Given the time-varying investor sentiment, we predict that token creators will cater – they create more tokens with the more popular meme keywords. The results show that a one-standard-deviation increase of the past 14-day meme-style return is associated with an up to 5% increase in the number of newly issued tokens and up to 17.0% increase in total trading volume of the meme-style. Not surprisingly, creators make more profit from

[2] In the case of GameStop, the company issued equity that significantly reduced its default probability.

such creations. Higher creator profit is equivalent to others' loss, as almost all the meme tokens become worthless in two or three days.

We further study an important source of creators' profits. Exit scams, also called rug pulls in the cryptocurrency community, are one type of fraud pervasive in DeFi. We find that meme-style index returns predict more frequent rug pulls in the future and higher overall rug pull profits. A one-standard-deviation increase in the meme-style index return is associated with a 3.4-4.4% increase in the number of new rug pulls and an 8.7-12.8% increase in rug pull profits. Such large economic magnitudes suggest that creators often exploit the investors who chase returns generated by meme tokens.

Given the low cost of entry, as time goes by, token creation becomes more competitive and attracting investor attention will become more difficult. According to salience theory (Bordalo et al., 2012, 2013), the attention of decision-makers is drawn to the most unusual, surprising, or salient attributes of the options they face, leading them to overweight these attributes in their decisions. We expect that in the later period of our sample, creators will create tokens with more unusual, surprising, or salient attributes. Consistently, we find that the price of tokens decreases from $2.6*10^{-3}$ BNB to $1.3*10^{-12}$ BNB in our sample period. Also, tokens are more likely to have two or more meme keywords – having more keywords will increase the chance of being noticed due to the design of the BSC trading.

Another finding is that, while most meme tokens lose investor interest in two or three days, a small number of meme tokens have persistent investor interest – a positive volume and price for a long period of time. Besides the well-known DogeCoin, several other such tokens exist, such as Shiba Inu and Floki. We are not aware of any existing theories that explain such a market structure – a small number of actively-traded meme tokens and a large number of short-life tokens. Any theory attempting to explain the meme phenomenon should be able to generate the co-existence of such dramatically different equilibria.

Pedersen (2022) emphasizes the importance of influencers and thought leaders in understanding the GameStop event. In the crypto market, a natural influencer is Elon Musk. From his Twitter account, we collect 27 tweets on DogeCoin, his favorite meme token. We find that, in response to his tweets, relative to non-Doge tokens, tokens with doge keyword experience increases in price, volume, and issuance. Immediately following the tweet, the relative increases in price, volume, and issuance are more than 10%, 40%, and 20%, respectively. Such increases persist for several days.

Meme stocks and meme tokens exhibit remarkable similarities. Due to the small number of meme stocks, some observations on them are necessarily more anecdotal. Similar to meme stocks, meme tokens experience dramatic price changes, and dramatic price changes are associated with abnormally high volume. The price increases tend to be sharp, and the price decreases are more gradual. For the long-life meme tokens, just like meme stocks, volatile and calm episodes are distinct and easy to tell. Like meme tokens, different meme stocks do not experience the meme episodes at the same time, also indicating switching investment sentiments.

We contribute to the new phenomenon of meme investment. The existence of meme assets and their return patterns challenge traditional finance theories. Meme assets, at least for meme tokens, are clearly without any fundamental value, and the majority of them have a very short life. However, millions of investors are attracted to such assets with billions of trading volume. We conjecture that social psychology, pioneered by Hirshleifer (2020) and Pedersen (2022), may help us understand some of our findings, as confirmed by our anlaysis of Elon Musk's tweets. However, to the best of our knowledge, none of the existing models can explain all of our findings, and we await more studies on these puzzling findings.

We contribute to the literature that studies how attention affects asset pricing. Models of attention-induced trading and returns predict that periods of intense buying will be followed by negative abnormal returns (Barber and Odean, 2008; Pedersen, 2022). Barber and Odean (2008), Da, Engelberg, and Gao (2011), and Barber, Huang, Odean, and Schwarz (2022), among others, document evidence consistent with such a prediction. Most of the studies are conducted in the stock market, where the supply of assets is relatively constant in the time span that attention plays a role. However, in our setting, asset supply is much more elastic and the effect of attention is mainly absorbed by asset supply.

Our study is also related to the literature on how managers cater to investor demands. There is a well-established literature on catering (Ben-David et al., 2022; Cooper et al., 2001; Lee, Shleifer, and Thaler, 1991; Baker and Wurgler, 2002; Barker, Greenwood, and Wurgler, 2009; Greenwood, Hanson, and Stein, 2010; Harris, Hartzmark, and Solomon, 2015). In our study, investor demands vary across different meme styles without any economic differences, while the existing studies focus on investment demand changes across more economically meaningful dimensions, such as book-to-market ratio or dividend.

Finally, our study is related to the growing literature on decentralized finance. Cong, Tang, Wang, and Zhao (2022) provide the first comprehensive analysis of the Ethereum DeFi ecosystem. Several studies investigate the properties of automated market makers (AMM) (e.g., Aoyagi, 2021; Capponi and Jia, 2021; Han, Huang, and Zhong, 2021; Foley, O'Neill, and Putnins, 2022; Hasbrouck, Saleh, and Rivera, 2022, Lehar and Parlour, 2021; Park, 2021). Unlike many papers that investigate specific properties of technologies implemented in DeFi platforms (e.g., AMM), our paper studies an unintended consequence of technological innovations in the blockchain economy: active trading of meme tokens and associated investor loss.

2. Institutional background

2.1 BNB Smart Chain

BNB Smart Chain (BSC), formerly known as Binance Smart Chain, is a blockchain that runs in parallel to the BNB Chain (formerly know as Binance Chain), which is Binance's dedicated blockchain for facilitating fast, decentralized transactions within the Binance ecosystem. Unlike BNB Chain, however, BSC boasts smart contract functionality and compatibility with the Ethereum Virtual Machine (EVM).

Because BSC is fully EVM-compatible, it supports the rich universe of Ethereum tools and DApps, including the popular DeFi wallets Metamask and Trust Wallet.[3] Moreover, BSC features pre-integrated price oracles (e.g. Chainlink) that are important for DApps of various types.[4] This level of compatibility makes it easy for DApp developers to switch from Ethereum to BSC. BEP-20 tokens are the standard framework for launching BSC tokens, which is similar to the Ethereum ERC-20 token standard. It is important to note that Binance's native token, BNB (formerly known as Binance Coin), is not compatible with the BEP-20 standard. Therefore, users need to use a DeFi wallet to convert their BNB to wrapped BNB before using them on BSC.

[3] BSC is a hard fork of the Go Ethereum (Geth) protocol and essentially uses the same codebase as Ethereum. The public wallet addresses are also the same for both BSC and Ethereum. For more information about BSC, see https://www.bnbchain.org/en/smartChain.

[4] Blockchain oracles are third-party services that feed the smart contract with external information that can trigger predefined actions of the smart contract. They serve as bridges between blockchains and the outside world.

BSC achieves roughly 3-second block times with a variant of proof-of-stake (PoS) consensus model. Specifically, it uses a proof-of-staked-authority algorithm, where participants stake their WBNB to become validators and vote on community governance protocols. The PoS model enables BSC to process transactions faster, putting it above networks that still implement proof-of-work (PoW) systems, such as the current Ethereum system. Completing a transaction on the Ethereum blockchain took between 30 seconds and 16 minutes as of late August 2021 (Jain, 2021).

Ethereum's congestion and high gas fees since the second half of 2020, thanks to the surging popularity of DeFi and NFTs, have pushed developers and staking investors to look for alternative networks. BSC, along with its decentralized exchange (DEX) PancakeSwap, cashed in on this migration. In addition to its fast speed, the BSC network has also attracted a significant number of users for its low cost (other more affordable alternatives include Polkadot, Cardano, and Solana). BSC's average gas fee, at 6.5 Gwei or 6.5×10^{-9} WBNB as of October 1, 2021, was significantly lower than that on Ethereum (BscScan, 2021).[5] As a result, during the first half of 2021, for example, the average fee associated with BSC transactions was only \$0.33, compared to Ethereum's average transaction fee of \$14.7 (BscScan, 2021; Etherscan, 2021).[6] As of October 1, 2021, the number of daily active BSC addresses was 1,045,127, nearly double Ethereum's 527,158 unique addresses.

2.2 PancakeSwap

[5] As the WBNB price continued to rise during the first half of 2021, the BSC community made the network more appealing to new users by lowering its minimum gas fee from 15 Gwei to 10 Gwei on February 10, 2021 and again to 5 Gwei on April 7, 2021.

[6] Since BscScan provides only daily total transaction fee (in WBNB) and the total number of transactions per day, we first calculate daily average transaction fee (in WBNB) by taking the ratio of these two numbers. We then multiply it by WBNB's daily USD close price from CoinMarketCap to compute the daily average transaction fee in USD.

The ascent of BSC since September 2020 cannot be described properly without mentioning PancakeSwap, which is the leading decentralized exchange (DEX) on BSC. As of October 2021, PancakeSwap claimed to be the most popular decentralized platform, with over 2.8 million users and $15 billion in total value locked (PancakeSwap, 2021). We compare PancakeSwap with other DEXs and centralized exchanges (CEXs) in Appendix I.

PancakeSwap uses an automated market maker (AMM) model to trade BEP-20 tokens. On such an AMM platform, instead of relying on an order book that matches orders, users trade against a permissionless liquidity pool run by smart contracts.[7] Each liquidity pool consists of a distinct pair of assets. When a liquidity pool is created, a liquidity provider (LP) sets the initial exchange rate for the two assets and supplies an equal value of both tokens to the pool.[8] This concept of an equal supply of both assets also applies to other users who are willing to supply liquidity to the pool. In return, an LP receives a pool-specific token called LP token in proportion to how much liquidity she supplies to the pool. For example, if ETH and BNB are added to a pool, the liquidity supplier receives ETH-BNB LP tokens. When a trade is facilitated by the pool, the trader pays a transaction fee that is proportionally distributed among all the LP token holders. An LP can withdraw her share of the pool by redeeming her LP tokens. In Internet Appendix II, we use an example to illustrate AMM mechanisms.

2.3 Creating and listing BSC tokens on PancakeSwap

There are a number of "token generator" websites for users to create BEP-20 tokens.[9] For a fee up to several BNB, a user can generate a standard BSC-based token (with a

[7] For a detailed discussion of the differences between AMMs and centralized limit order markets, the reader is referred to Lehar and Parlour (2021).

[8] If the initial exchange ratio of the tokens in the pool diverges from the current global market price, there exists an instant arbitrage opportunity that can result in capital loss for the liquidity provider.

[9] A token generator can be access via https://vittominacori.github.io/bep20-generator/.

capped total supply and the ability to burn tokens) within minutes. The basic steps include (1) creating a wallet using DApps such as MetaMask or Trust Wallet to pay for contract deployment on the blockchain, (2) choosing token name, symbol, and total supply, among other parameters, and (3) confirming the transaction and deploying the token on the BSC.

There is no listing fee on BSC as opposed to listing fees on a CEX (see Lee, Li, and Shin (2022) for a detailed discussion of listing tokens on CEXs). To list a token, a creator navigates to PancakeSwap using a Web3 browser, such as MetaMask or Trust Wallet, and clicks the Liquidity button. He then locates the newly created contract address, adds the token and the numeraire (BNB or any other token), and supplies the amount of the pair, the ratio of which determines the price of the token. Lastly, the creator confirms the details and presses the Create Pool & Supply button.[10]

2.4 Promoting newly created BSC tokens

Around the time a BSC token is issued and goes live on PancakeSwap, the creator may choose to promote on Reddit, Telegram, and/or other social media platforms. For example, creators, their related parties or third parties often advertise new tokens in popular subreddits, such as CryptoMoonShots, which had nearly 1.9 million members as of February 2023. A typical advertisement features a brief introduction to the token, key tokenomics metrics including total supply and transaction tax, and whether LP tokens are locked, among other details.[11] The contract address and links to the token's social media sites are

[10] See https://medium.com/memecoingen/how-to-list-your-coin-on-pancakeswap-7b1ddc82f4cc for a visual guide for listing tokens on PancakeSwap.

[11] This advertisement features Moon Lab, one of the BSC tokens in our sample: https://www.reddit.com/r/CryptoMoonShots/comments/o2okgv/mlab_stealth_launched_devs_havent_sold_and/

provided. Many tokens have their dedicated Telegram channels. Often, the advertisement also provides a link to the trading pair on PancakeSwap.

2.5 Trading BSC tokens

To trade tokens on PancakeSwap, a trader first needs to connect his wallet to PancakeSwap on the Swap page. Given the base currency (e.g. BNB) and amount (e.g. 1 BNB), the trader chooses the token he wants to trade to by either typing in the token name or address on the "Select a Token" window. He then confirms the trade to complete the swap. Understanding that BSC can feature multiple tokens with the same name, seasoned traders would use the address to search for a token. However, inexperienced traders may search using a token name instead. For example, searching for "doge" will generate more than 10 distinct tokens that contain "doge" in their names.

3. Data

3.1 Price and trading volume data

We use a proprietary API to collect token price data from liquidity pools on PancakeSwap (Versions 1 and 2). We find that the vast majority of tokens are swapped with major numeraire cryptocurrencies in the following order depending on their popularity: (1) Wrapped BNB (BNB), (2) Binance USD (BUSD), (3) PancakeSwap token (CAKE), (4) Ethereum (ETH), (5) Bitcoin (BTC), (6) Tether (USDT), (7) USD Coin (USDC), and (8) MakerDAO's DAI token (DAI). Among them, in our research, we focus on tokens whose numeraire is BNB because BNB accounts for 94% of all numeraires.

Token prices are recorded in BNB. If a token (e.g. T) is swapped with BNB, we use the most recent transaction at the end of each day (GMT) to define the transaction price.

The price equals the amount of BNB transferred divided by the amount of token T transferred. If a token is not traded on a specific date, we use the most recent price as of that date. We measure daily trading volume in BNB by multiplying the daily amount of token T transferred through PancakeSwap's liquidity pools by T's price in BNB.

3.2 Token contract data

We download each token's verified source code and creator address from BscScan. Creators of 66.7% of our sample tokens chose to publish their source codes through a verification process. We also obtain several contract-specific variables from the Binance Smart Chain and TokenSniffer.com, a major crypto forensic firm. These variables include the fraction of tokens retained by the creator, the number of outstanding tokens, the number of LP tokens burned, the number of outstanding LP tokens immediately after the first liquidity provision, and whether the creator renounced ownership (so the creator does not have special access to the contract/code).

3.3 Social media data (Reddit and Telegram advertisements)

Using a Python script to search the addresses of the 584,427 DEX-traded tokens issued by December 31, 2021 on Reddit and Telegram, we download all posts that contain these addresses. We find that 26,864 and 7,185 unique tokens are advertised on Reddit and Telegram, respectively.

4. Meme-token definition, key variables, and sample description

4.1 Defining meme tokens

Meme is a newly coined word and broadly defined as "an amusing or interesting item (such as a captioned picture or video) or genre of items that is spread widely online especially through social media" (Merriam-Webster, 2022).[12] In the cryptocurrency market, token creators appear to use funny names, emojis, or images to attract investors' attention. One example is DogeCoin, which was created in 2013 by two IBM engineers for fun (Kay, 2021).[13] It used the doge meme, a funny image of a Shiba Inu, which went viral on the internet during that time.

We obtain our list of meme tokens from BSC. Although many believe that most BSC tokens are meme tokens, we apply several filters to obtain a clean and conservative sample of meme tokens. These filters are described below, along with the number of meme tokens that remain in our sample (in parentheses) after each filter is applied.

1. It is a token issued on BSC. (901,374 tokens)
2. It has a noun in the token name that appears at least 50 times during our sample period. We focus on nouns because a verb is unlikely to be a meme keyword. (537,991 tokens)
3. It is a token that has a liquidity pool with positive liquidity on PancakeSwap. (383,802 tokens)
4. We group these keywords into 110 categories based on common characteristics and meanings. We closely examine each category and exclude those that are less likely to be a meme.
    a. First, we exclude several categories that are potentially related to businesses using blockchain technology and/or cryptocurrencies: coin/token, currency, game, gamble, and money. We are left with 105 categories. (349,607 tokens)
    b. Second, we eliminate ambiguous categories and categories that might have fundamentals. We end up with 61 categories. (312,398 tokens)

[12] See https://www.merriam-webster.com/dictionary/meme

5. We further exclude potential business-related tokens featured on multiple websites, the coverages of which are not mutually exclusive.
   a. First, CoinMarketCap features a set of large BSC tokens and classifies them into meme and non-meme tokens. We drop tokens classified as non-meme tokens by CoinMarketCap. (311,888 tokens)
   b. Second, BscScan.com features tokens of large market capitalization. Among 474 largest tokens featured on BscScan, we read the description of each token and exclude 460 non-meme tokens. (311,861 tokens)
   c. We drop tokens that are classified as decentralized applications (dApps) by DappRadar.[14] DappRadar is a dashboard that features dApps deployed on major blockchains and has been used as a main data source for academic research on decentralized applications (i.e., Cong, Tang, Wang, and Zhao, 2022; Wu, 2019).[15] We identify 3,070 tokens that are associated with dApps projects built on BSC. (311,440 tokens)
6. Finally, we check whether tokens with the highest trading volumes are possibly business-related. Specifically, for each meme keyword we select the two tokens that have the largest trading volumes. We manually check their official websites via BscScan and other sources, including white papers and social media accounts. If any of these sources claims that a token is associated with DeFi applications, we exclude

[14] Not all the tokens on DappRadar are non-meme. DappRadar classifies dApps into Collectibles, DeFi, Exchanges, Gambling, Games, High-Risk, Marketplaces, Social, and Other. We find that a small number of tokens in the High Risk category are likely meme tokens. Nevertheless, we drop all of them to be conservative.
[15] DappRadar does not have token addresses for all dApp tokens. For dApp tokens without an address on DappRadar, we manually search the project name and the website on BSCscan. If the information displayed on DappRadar and BSCscan is consistent with each other, we use the token address provided by BscScan.

it from our sample. We find that 86 out of the 1,088 unique tokens have business purposes.[16] (311,354 tokens)

7. Our final sample contains 311,354 meme tokens, with a total trading volume of $30.5 billion.

Admittedly, determining whether a given token is a meme token or not depends on some subjective decisions. As a sanity check, we compare how many categories in our meme keyword categories overlap with the keyword categories of CoinMarketCap and four other popular cryptocurrency websites that identify meme tokens (CoinGecko.com, crypto.com, coinranking.com, and cryptoslate.com). We find that out of our 61 meme categories, 32 are covered by these websites. Over 98% of meme tokens in our final sample are covered by the 32 categories, which demonstrates that our sample represents meme tokens perceived by the cryptocurrency industry.

4.2 Key variables

4.2.1. Meme-style indices

We construct return indices for the 557 meme styles (i.e. keywords) in our final sample. To study style-specific returns, we drop tokens whose names contain multiple keywords. This step yields 241,438 tokens, which account for 78% of our sample tokens. As token returns are highly skewed, we winsorize individual tokens' daily returns by setting returns lower than -99% to -99% and returns higher than 1,000% to 1,000%. In addition, we drop

[16] BscScan classifies a group of tokens into the "Binance-Peg" category, which are "tokens that are wrapped and pegged by Binance on a 1:1 ratio to the corresponding native token." We identify 66 Binance-Peg tokens. Only two of them, Doge and Shiba Inu, are in our sample as of Step 6. Given that these are clear meme coins, we do not drop them.

tokens that are inactive consecutively for at least three days. To further eliminate outliers, we drop tokens whose daily trading volume is zero on any of the past seven days and tokens that are created within the last seven days. We create both volume-weighted (by trading volume over the past seven days) and equal-weighted index returns, with the latter being used for regression analyses.

4.2.2 Creators' profits

Suppose creator C creates a token T on a specific date. C then deposits token T and BNB to create a liquidity pool. In return, C will receive some LP tokens, which represent her stake in the pool. As mentioned in Section 2, C can withdraw her share of the pool (BNB and T) by redeeming her LP tokens. We download all of C's transactions involving the LP, T, and BNB tokens since the token creation date. Liquidity provision leads to outflows of T and BNB from C's wallet while redemptions result in inflows of T and BNB. This enables us to compute C's net balance of BNB tokens as a result of liquidity provision and redemptions.

In addition to receiving BNB by redeeming LP tokens, C can also obtain BNB by selling token T (sending T to the liquidity pool) or receive T by selling BNB. We calculate the net balance of BNB tokens that C receives from such swap transactions. We then calculate C's total profit made from token T by summing the net balance of BNB tokens associated with both liquidity provision and trading activities. Specifically, we compute the net balance of BNB tokens C generates during the window [0, D], where D equals 1, 2, 3, 4, 5, 7, 14, and 28 days after token creation.

4.2.3 Rug pull profits

An important part of creators' profits are generated through a "rug pull," which is a malicious maneuver where the creator suddenly drains all the liquidity (e.g. BNB or another numeraire) from a liquidity pool, leaving traders with worthless tokens (Mackintosh, 2021). This is an extreme form of LP-token redemption. We define a token a rug pull if 90% of liquidity is redeemed within a short window post-issuance, such as five days. Varying the percentage of liquidity drained and the window after issuance yields consistent results.

In the most intuitive case, the creator is the sole liquidity provider. However, the creator can send LP tokens to collaborators who also serve as liquidity providers. We thus measure rug-pull profit as the total amount of a numeraire withdrawn within five days after issuance. Appendix II details our procedure to calculate rug pull profits for each token, an example of actual rug pulls (LAMBO token), and summary statistics on rug pulls on BSC.

4.2.4. The similarity measure

We use the similarity of two tokens' source codes to proxy for their similarity. We first remove comments and empty lines in the raw source codes because they are not essential to the functioning of tokens. We then compute a Jaccard similarity index for each pair of tokens. Jaccard similarity ranges from 0 to 1, where 1 implies that the two codes are identical and 0 means that the codes have no overlap.[17]

4.3 Sample description

Between the inception of BSC on September 12, 2020 and December 31, 2021, 901,374 tokens were issued on BSC, excluding LP tokens. However, not all tokens are traded on DEXs. For example, some tokens are created for testing specific projects. Among these tokens, 584,427 tokens were traded at least once on DEXs, accounting for 64.7% of all issued tokens. As shown in Figure 1, Panel A, the daily issuances of traded tokens and meme

[17] Our personal computers were not able to analyze the large number of source-code pairs. We therefore perform parallel processing using HiPerGator, the University of Florida's research computing resource. It took us approximately three days to compute Jaccard similarity indexes for all source-code pairs.

tokens are highly correlated during 2021, both of which reached their peaks around May 2021 when prices of major cryptocurrencies were close to their all-time highs. Panel B shows that for meme tokens, the number of new issues and trading volume are positively related.

[Insert Figure 1 here.]

Figure 2 plots the percent of tokens that are similar to at least one previously issued token. Relying on the Jaccard similarity index for verified source codes, we find that 90.5% of tokens are at least 95% similar to a previously issued token. Raising the similarity index to 99%, we show that still 55.5% of the tokens are similar to a previously issued token.

[Insert Figure 2 here.]

Figure 3 demonstrates the dominance of serial issuers on BSC. For example, the 10% most prolific creators issued about 50% of all meme tokens. The most prolific creator, whose address is 0x608756c184a0723077b0c10f97f4d054c9ee1c0f, issued 15,537 tokens during our sample period. Such a skewed pattern of token issuance suggests the importance of serial issuers in the meme-token market.

[Insert Figure 3 here.]

Consistent with the above pattern on serial creators, Table 1 shows that the average creator issued 354 meme tokens before the current one while the median number of previously issued tokens is only one. On average, a token has nearly 500 similar tokens, based on a Jaccard similarity index of 99% or above for source codes. However, the median figure is only one. These statistics suggest that serial creators tend to issue identical tokens. Interestingly, 5.4% of the meme tokens are advertised on Reddit or Telegram, with an intention to attract retail investors.

[Insert Table 1 here.]

Regarding meme tokens' ex-post characteristics, the average (median) trading volume for the first 30 days after issuance is \$56,503 (\$170), indicating the dominance of largest tokens. Creators' profits exhibit a similarly skewed distribution—the average (median) creator profit is \$430 (\$11). Perhaps surprisingly, in 62% of the tokens, investors are victims of rug pull scams. Rug pulls on average contribute to the majority of creators' profits—the average and median rug pull profits are \$406 and \$4.2, respectively. Importantly, on average 96% of the first month's trading volume takes place in the first two days, with only 9.2% of the first 30 days seeing non-zero trading. Figure 4 paints a more granular picture. For the largest 5% of tokens (based on trading volume), their trading volumes drop to near zero in two days post-issuance. Even for the top 1% of tokens, which are the most successful ones, their trading volume becomes close to zero in about two weeks. These patterns are reminiscent of pump-and-dump schemes that are documented in Li, Shin, and Wang (2022).

[Insert Figure 4 here.]

5. Empirical Results

5.1 Meme styles

To examine whether token returns are related to meme styles, we choose tokens from the top 12 meme styles based on the total trading volume of their constituent tokens. We then calculate the cumulative return index for each meme style and plot these indices in Figure 5. Shiba-themed tokens generated the highest cumulative returns during our sample period, while Squid-themed tokens were the worst performers, with Floki-themed tokens being in the middle of the pack (Floki is the name of Elon Musk's pet Shiba Inu). This pattern shows that different meme styles exhibit different return dynamics, which serves as the basis for our further analyses.

[Insert Figure 5 here.]

Next, we investigate whether a meme token's performance is correlated with other tokens belonging to the same meme style. For this purpose, we estimate the following regression model.

$$Ret_{i,t} = \alpha + \beta_1 \frac{1}{N} \sum_{j \neq i} Ret_{i,t} + \beta_2 \frac{1}{N_m} \sum_{j \neq i \& j \in m} Ret_{i,t} + \varepsilon_{i,t}$$

where i and t index token and day. The *token index return*, $\frac{1}{N} \sum_{j \neq i} Ret_{i,t}$, is the average return across all the tokens except the focal one. The *meme-style index return*, $\frac{1}{N_m} \sum_{j \neq i \& j \in c} Ret_{i,t}$, is the average return across all the tokens with the same meme style except the focal one. In an alternative specification, we replace the second term with an index return for tokens with similar codes, where two tokens are considered to be similar if the Jaccard index of their source codes is greater than 0.99.

As shown in column (1) of Table 2, we find a positive relationship between an individual token's return and the meme-token index return. Column (2) shows that an individual token's return is also strongly correlated with its corresponding meme-style index return. Strong correlations are observed in alternative specifications. In column (3), we run a univariate regression with day fixed effects and in column (4) we run the same regression by including only tokens that have similar source codes. As shown in column (5), we also find a positive relationship between a token's return and the return of tokens with similar codes. Furthermore, we find qualitatively similar results using a sample consisting of the top 200 meme styles. Overall, our results suggest that a meme token's performance is correlated with tokens that belong to the same meme style and that have similar source codes.

[Insert Table 2 here.]

5.2 Past performance and future meme activities

In this subsection, we study how meme-style index returns affect future meme activities at the meme-style level, including the issuance of new meme tokens, trading volume, and creators' profits.

[Insert Table 3 here.]

As shown in columns (1) and (2) of Table 3, past meme-style index returns have a positive and statistically significant effect on the number of newly issued tokens adopting this style. This suggests that creators issue more meme tokens whose meme-style index performed well over the last 14 days, possibly because they cater to the investors who are excited about the outperformance of the meme-style index.

We also find that investors react to past performance of a meme-style index. As shown in columns (3) and (4), a one-standard-deviation increase in the meme-style index return is associated with a 13.9-17.0% increase in total trading volume of the meme-style. Finally, we find evidence that higher past meme-style index returns are associated with higher profits for token creators. As reported in columns (5) and (6), a one-standard-deviation increase in the meme-style index return translates into a 3.5-6.0% increase in creators' profits. In Table A5, we report results using newly issued tokens on the next day. In Table A6, we restrict our sample to the top 200 meme styles. Our results are robust when using these alternative samples.

We then conduct a similar analysis at the token level. As shown in Table 4, there is no significant relationship between meme-style index returns and a token's 30-day trading volume post-issuance or the creator's profit, implying that the positive relationships observed in Table 3 are mainly driven by a higher number of newly issued tokens rather than an increased trading volume and higher creator profit per token.

[Insert Table 4 here.]

Overall, our results suggest that creators cater to investors who chase good performance of a particular meme style by issuing more tokens with the same style. Consequently, the creators earn a higher average profit from these investors.

We further study an important source of creators' profits. Exit scams, also called rug pulls in the cryptocurrency community, are one type of fraud pervasive in DeFi. We report in Table 5 that meme-style index returns predict more frequent rug pulls in the future and higher overall rug pull profits. A one-standard-deviation increase in the meme-style index return is associated with a 3.4-4.4% increase in the number of new rug pulls and an 8.7-12.8% increase in rug pull profits. Such large economic magnitudes suggest that creators often exploit the investors who chase returns generated by meme tokens.

[Insert Table 5 here.]

5.3 Competition for attention

We examine creators' behavior when the meme-token market became more mature and competitive. As shown in Figure 6, Panel A, the number of meme styles exhibited in the average token's name kept rising during our sample period, from below 1.15 in January 2021 to above 1.3 in December 2021. In Appendix Table A4, we classify our tokens into several categories based on the number of meme style keywords. Consistent with the findings in Figure 6 Panel A, the fraction of meme tokens with only one meme style has consistently decreased from 87.3% to 72.3% while the fractions of meme tokens with two and three meme styles have increased.

In addition, Figure 6, Panel B shows that the issuance price for the average meme token kept dropping. These two findings are consistent with what the theory of competition for attention predicts. As the competition becomes fiercer, meme-token creators adopt salient features to make their newly-issued tokens more attractive: more meme keywords and a lower price.

[Insert Figure 6 here.]

5.4 Why do investors trade meme tokens?

We find that during our sample period, the overall trading volume of meme tokens is $30.5 billion. In addition, the average creator's profit per token is $430.0, an amount that is economically significant, which implies that the average meme-token trader loses money. A natural follow-up question is why investors trade meme tokens despite their average negative profit.

We conjecture two plausible mechanisms. The first potential mechanism is that meme tokens attract overconfident investors who believe they can time the market better than others can. As shown in Figure 4, the vast majority of meme tokens become worthless after a few days post-issuance: the top 5% of all tokens ceases trading within two days and even the top 1% suspends trading within two weeks. This suggests that only investors who time the market well by buying the tokens relatively early at a low price and selling them at a higher price can earn a profit. Therefore, investors who believe that they can time the market better than others would be willing to participate in meme-token trading (e.g. Barber and Odean, 2000, 2001; Scheinkman and Xiong, 2003).

Another plausible mechanism is that investors with gambling preferences participate in meme-token trading. The summary statistics reported in Table 1 suggest that the average first-day log return is negative while the 75 percentile return is over 50%. This suggests that although the average return is negative, investors can still earn very high short-term returns if they invest in the right meme tokens. In addition, as discussed in Section 4.3, creators have consistently lowered the nominal issuance price during our sample period to attract investors, with the average price being lower than 10^{-11} BNB at the end of our sample period. These basic empirical patterns suggest that investors with gambling preferences who overweight high short-term returns may participate in meme-token trading (Barberis and Huang, 2008; Bordalo, Gennaioli, and Shleifer, 2012, 2013; Barberis, Mukherjee, and Wang, 2016).

We follow standard approaches to create proxies for gambling preference and overconfidence. Our proxy for gambling preference is the median price of all the cryptocurrencies an investor has bought. Low-priced cryptocurrencies may seem "cheap" and have a large upside potential. Such a proxy has been used in the stock market (Kumar, 2009; Birru and Wang, 2016) and the cryptocurrency market (Li, Shin, and Wang, 2022). An alternative method is to estimate the skewness, which requires a long sample period. However, given that the life cycle of a meme token is, on average, very short (see Figure 4), we cannot estimate the skewness. Our proxy for overconfidence is trading frequency because it is known that overconfident investors trade more frequently than others (Barber and Odean, 2000, 2001; Scheinkman and Xiong, 2003). We measure trading frequency following Ben-David and Hirshleifer (2012). Specifically, we calculate the daily probability that an investor sells his positions. We also measure portfolio size, experience, and past returns of individual traders. We estimate these investor characteristics at the end of each month and predict who participates in meme-token trading the following month. Our general empirical approach is similar to that of Li, Shin, and Wang (2022), who study the motives of investors participating in cryptocurrency pump-and-dumps.

[Insert Table 6 here.]

In Table 6, Panel A, we report the summary statistics for our sample. For each variable, we first calculate its mean, the first quartile, its median, the third quartile, and the standard deviation for each month and then compute the average across months. On average, 17% of investors participate in meme-token trading each month. The average log (price) is -11.21 (about $1.35*10^{-5}$ BNB or $0.004), which is significantly lower than the average stock price (about $30). The average daily selling probability is 2.4%, about ten times higher than the daily selling probability for retail investors on the stock market (Ben-David and Hirshleifer, 2012).

The results reported in Table 6, Panel B are consistent with our conjectures that investors with overconfidence and gambling preferences are likely to participate in meme-token trading. We find that investors with a lower median purchase price and a higher selling probability are more likely to trade meme tokens. These results are robust to the inclusion of several control variables, such as portfolio size, experience, and investor returns. Our results are not driven by a few popular meme tokens, such as DogeCoin and Shiba Inu. In Table A7, we define an alternative dependent variable, *Participate in meme-token trading*, which is a dummy variable equal to 1 if an investor trades meme tokens that are not featured by CoinMarketCap, and 0 otherwise. We obtain qualitatively similar results.

6. Elon Musk's tweets

We collect Elon Musk's tweets from his Twitter profile and manually identify all the tweets on cryptos. His favorite meme token is DogeCoin. In the period from July 15, 2020 to December 31, 2022, he tweeted DogeCoin 27 times, either with the word "doge" or with a dog figure. We estimate Musk's tweets on meme tokens using a difference-in-differences strategy. Tokens with the "doge" keyword are treated and other non-doge meme tokens are controls.

$$\log(y_{i,t}) = \sum_{j=-5, j\neq -1}^{j=7} \beta_j Doge_i * I_j + \delta_{kj} + \gamma_i + \varepsilon_{i,t}$$

where k, i, t, and j index tweet, token, calendar day, and event day, respectively. $Doge_i$ is a dummy equal to 1 if token i has "doge" in its name and 0 otherwise. I_j is an indicator of event day j. We use day -1 as the base case. δ_{kj} and γ_i are tweet*event day fixed effects and token fixed effects. $y_{i,t}$ is price, volume, or issuance (i.e., the number of newly issued tokens). For issuance, we use the data from Binance Smart Chain. For price and volume analysis, we focus on the relatively well-established tokens that are listed on CoinMarketCap.

Figure 7 presents the β_j coefficients for price, volume, and issuance on the three panels, respectively. Obviously, Musk's tweets on DogeCoin increase the price, volume, and issuance of doge-related tokens more than non-doge-related tokens. On the first day after the tweet, relatively to non-doge-related tokens, the price, volume, and issuance of doge-related tokens increase by more than 10%, 40%, and 30%, respectively. Such increases persist for days. Before the tweets, we observe no detectable difference in price, volume, or issuance between doge-related and non-doge-related tokens. Such tests serve as parallel trend tests and indicate that the non-doge-tokens are reasonable controls. These findings confirm the importance of influencers in understanding meme investment.

7. Conclusions

We study the meme tokens in the cryptocurrency market, which generated a huge trading volume in 2021. We find that investors' interest in different meme styles changes over time, and there exists correlation between returns of tokens with the same meme keywords. Token creators cater to the demand of meme investors by issuing more tokens with the popular keywords and make more money from such issuances. We find evidence that is consistent with competition for attention theory.

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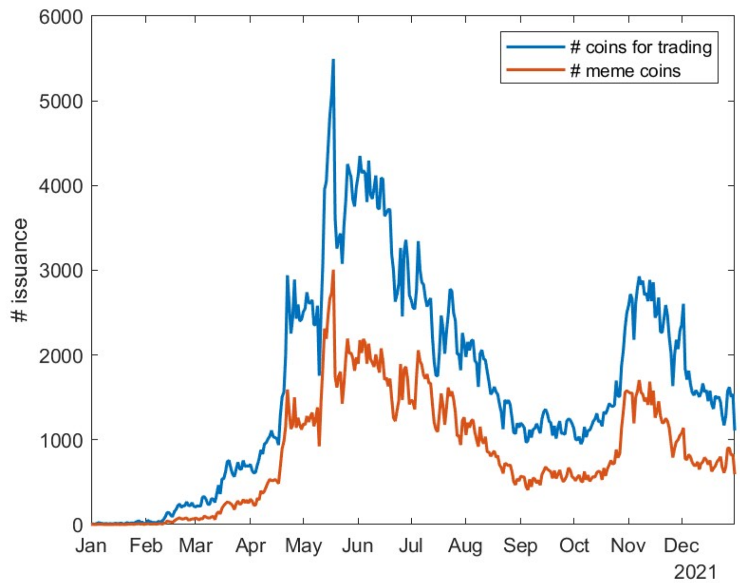
Figure 1. Issuance and trading volume of meme tokens

In this figure, we display the patterns of issuance and trading volume of meme tokens. In Panel A, the blue line plots the number of tokens issued for trading and the red line plots the number of meme tokens issued for trading. In Panel B, we overlay the number of issued meme tokens in red and their trading volume in purple.

Panel A: Token issuance trends



Panel B: # of meme tokens and trading volume

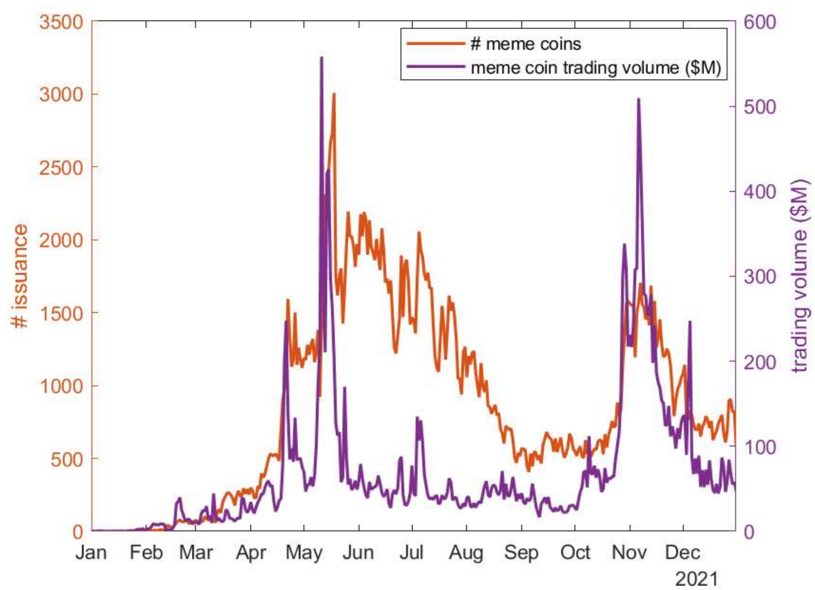


Figure 2. Number of Tokens that Have Similar Tokens

We compute the number of similar tokens created before for all the tokens with verified source codes. In this figure, we plot the percentages of tokens that have similar tokens based on different criteria. For example, similarity ≥98% means that we define two tokens are similar if the Jaccard similarity index is greater than or equal to 98%. We display the results in the blue bars using the selection criteria with thresholds of 95, 98, and 99%.

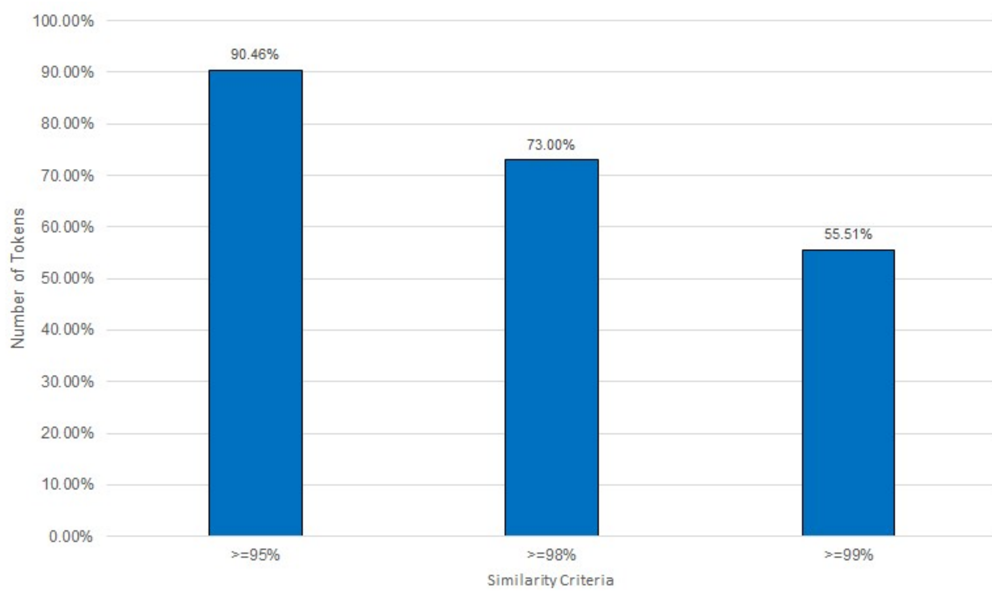


Figure 3. Cumulative percentage of the number of tokens by creators

In these figures, we plot the cumulative percentage of the number of tokens by creators and clusters. To construct the figure, we sort the creators by the number of issued tokens in a descending order. Then, we define the cumulative percentage of the number of tokens as the number of cumulative tokens divided by the token number of tokens and we convert it to a percentage unit by multiplying 100. The red vertical line plots the percentage of creators for which the cumulative percentage of the number of tokens is 50%.

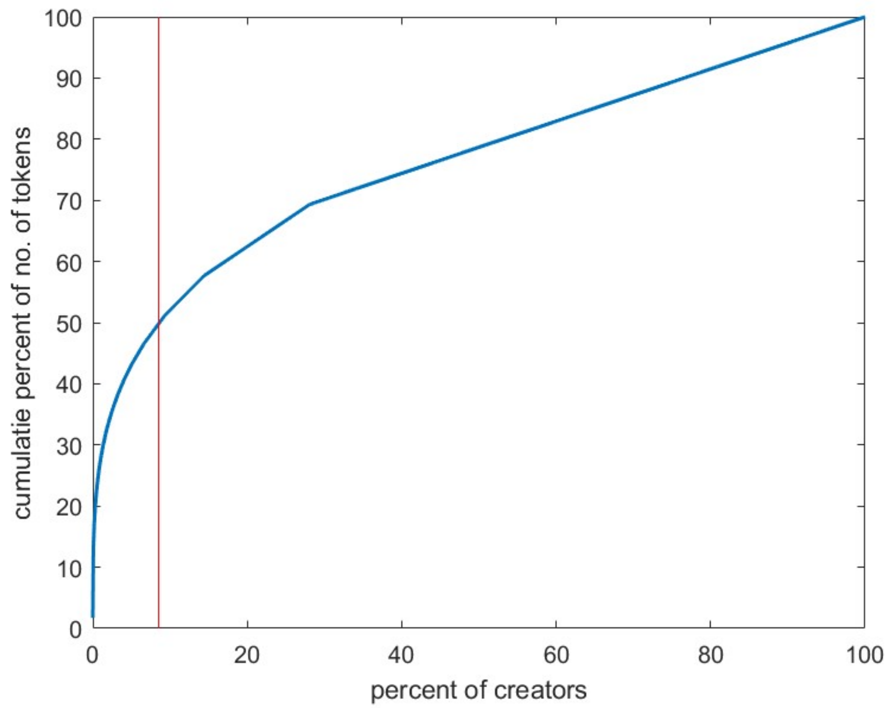


Figure 4. Trading volume of meme tokens

In this figure, we investigate the dynamics of trading volume of meme tokens. For each token, we compute the normalized trading volume defined as the trading volume on day t (t=1, 2, …, 30) divided by the first day trading volume. Then, we compute 50, 90, 95, and 99 percentiles of the normalized trading volumes on each day. The blue, red, yellow, and purple lines plots 50, 90, 95, and 99 percentiles of the normalized trading volume.

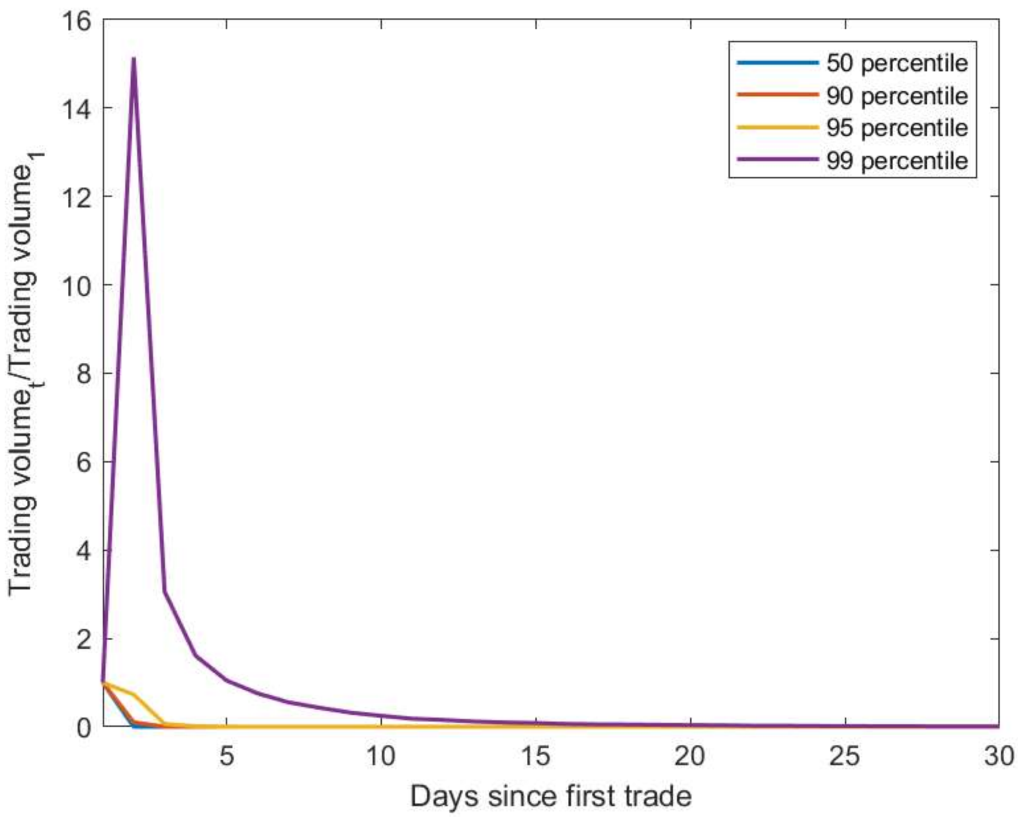


Figure 5. Meme-style index cumulative returns

In this figure, we plots the cumulative returns of each meme-style index. We choose top 12 meme-style indices based on the total trading volume of all tokens in each meme style.

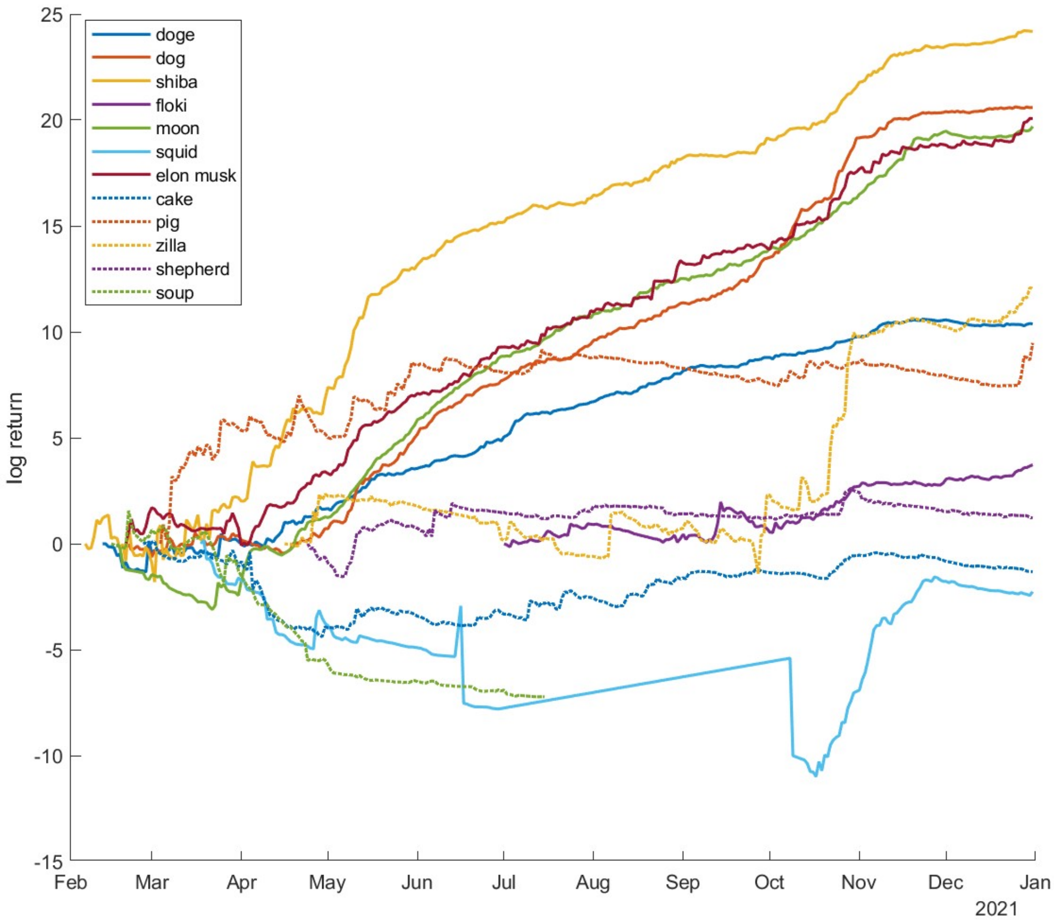
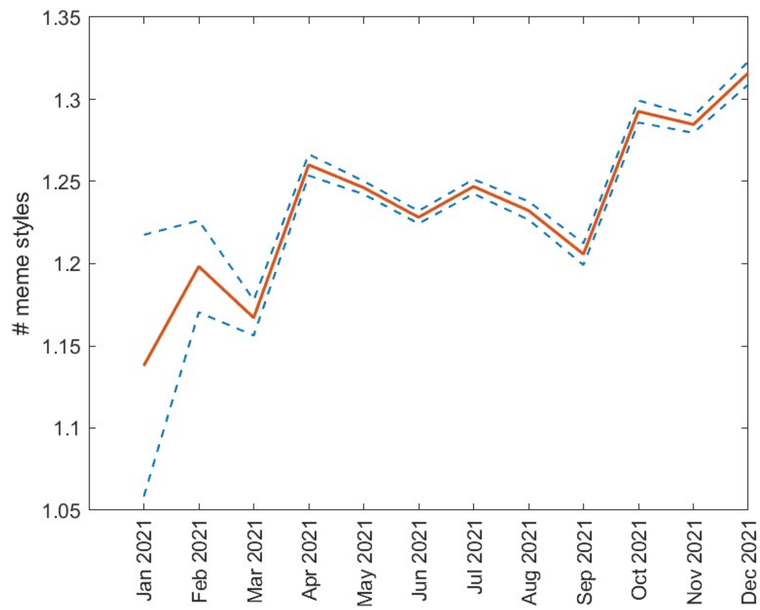


Figure 6. Competition for attention

In this figure, we show how creators of meme tokens use several token features to compete for investors' attention. In Panel A, we plot the average number of meme styles of meme tokens in each month. In Panel B, we plot the average logarithm with base of 10 of initial prices of meme tokens in each month. The blue dashed lines are 95% confidence intervals.

Panel A. The number of meme styles



Panel B. Logarithm of initial price

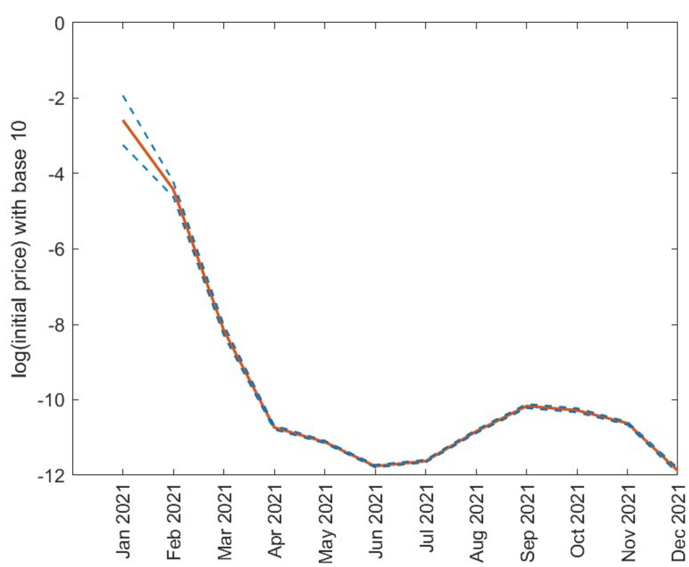


Figure 7. Elon Musk's tweets

In this figure, we present the β_j coefficients of the following regression where the dependent variable is either price (Panel A), volume (Panel B), or issuance (Panel C).

$$\log(y_{i,t}) = \sum_{j=-5, j\neq -1}^{j=7} \beta_j Doge_i * I_j + \delta_{kj} + \gamma_i + \varepsilon_{i,t}$$

where k, i, t, and j index tweet, token, calendar day, and event day, respectively. $Doge_i$ is a dummy equal to 1 if token i has "doge" in its name and 0 otherwise. I_j is an indicator of event day j. We use day -1 as the base case. δ_{kj} and γ_i are tweet*event day fixed effects and token fixed effects. $y_{i,t}$ is price, volume, or issuance.

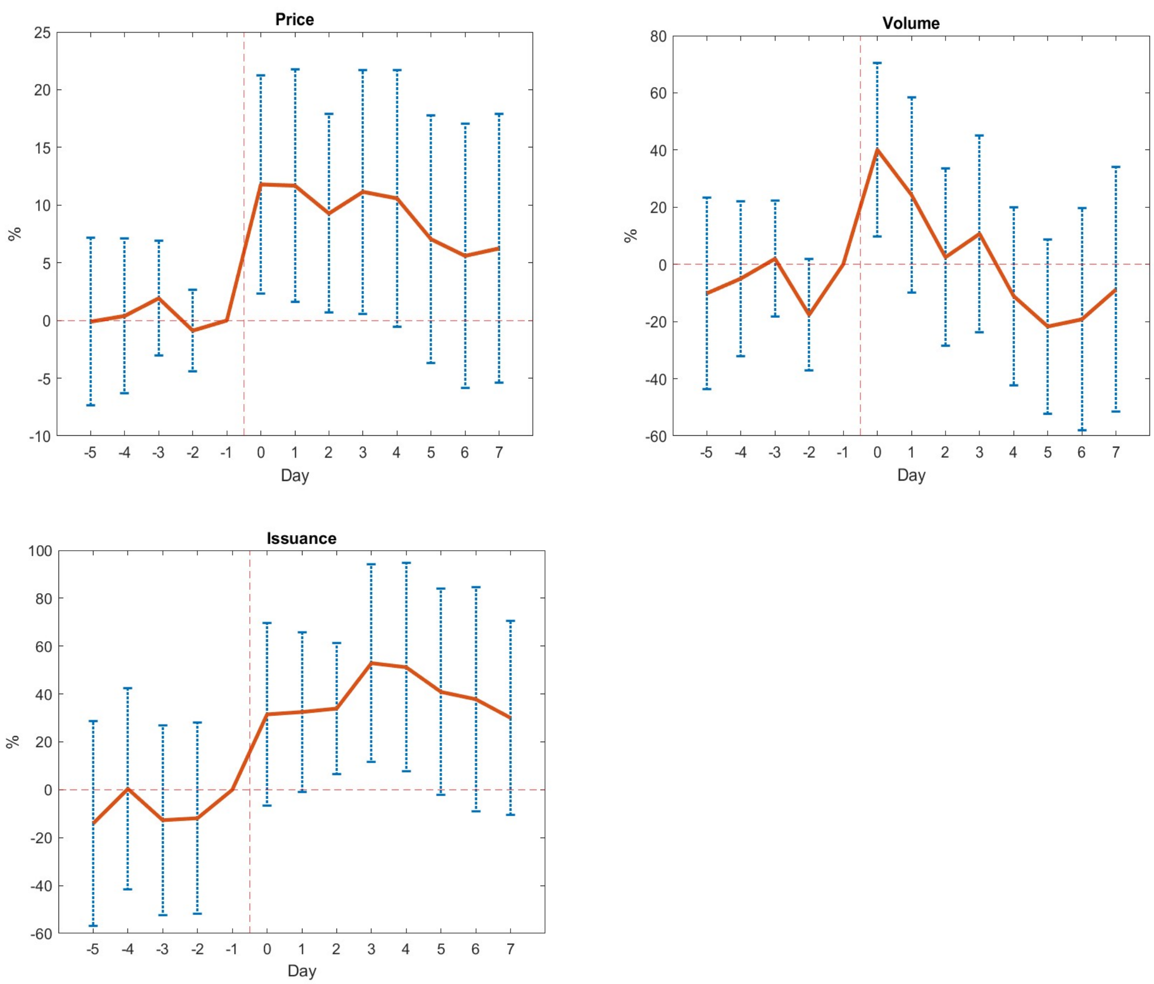


Table 1. Summary Statistics

In this table, we provide summary statistics of token characteristics. *# tokens issued by the same creator* is the number of previously tokens issued by the same creator. *Length of source code* is the number of characters in the source code. *No. of similar tokens* is the number of previously issued tokens whose Jaccard similarity measures are greater than 0.99. *Fraction of tokens retained* is the number of tokens in the token creator's wallet divided by the number of tokens issued. *Fraction of LP tokens burned* is the number of burned LP tokens divided by the total number of LP tokens outstanding right after the first liquidity provision. *Ownership renouncement* is a dummy variable equal to 1 if ownership is renounced and 0 otherwise. *Initial token price* is the price of the token in BNB right after the first liquidity provision. *Advertised in social media* is a dummy variable equal to 1 if a given token is announced in Reddit or Telegram and 0 otherwise. *Trading volume ($) for the first 30 days* is the dollar value of the trading volume over the first 30 days since creation. *Creator's profit ($) for the first 30 days* is the dollar value of the creator's profit for the first 30 days since creation. *Is rug pull* is a dummy variable equal to 1 if a token is a rug pull, and 0 otherwise. *Rug pull profit ($)* is the dollar value of creator's profit in a rug pull. *Fraction of the first two-day volume over the 30-day volume* is the trading volume over the first two days divided by trading volume over the first 30 days since creation. *Fraction of the days with positive volumes for the first 30 days* is the number of days with positive trading volumes over the first 30 days since creation divided by 30. *First day log return* is the logarithm of first day close price divided by initial price measured in BNB.

	Average	Q1	Median	Q3	SD	N
Ex-ante variables						
# tokens issued by same creator before	354.063	0	1	14	1667.487	311,354
Length of source code	16,864.938	7,149	11,443	29,895	12,112.837	207,524
No. of similar tokens	459.835	0	1	49	1,628.057	207,524
Fraction of tokens retained	0.183	0	0	0.200	0.331	299,640
Fraction of LP token burned	0.047	0	0	0	0.211	302,051
Ownership renouncement	0.213	0	0	0	0.409	255,518
Initial token price (in BNB)	$3.41*10^{-4}$	$1.00*10^{-14}$	$3.20*10^{-12}$	$4.21*10^{-9}$	0.003	304,461
Advertised in social media	0.054	0	0	0	0.226	311,354
Ex-post variables						
Trading volume ($) for the first 30 days	56,502.636	16.059	169.602	1,614.579	2,989,344.839	288,750
Creator's profit ($) for the first 30 days	430.252	0.111	11.107	103.289	11,408.894	288,750
Is rug pull	0.621	0	1	1	0.485	311,354
Rug pull profit ($)	405.595	0	4.233	63.633	5,744.198	311,354
Fraction of the first two-day volume over 30-day volume	0.958	0.999	1	1	0.158	296,373
Fraction of the days with positive volumes for the first 30 days	0.092	0.033	0.033	0.067	0.154	296,373
First day log return	-1.424	-0.290	0.046	0.566	6.022	277,921

Table 2. Token return similarity

In this table, we investigates the relationship between meme-token return and several index returns. *Token return* is the daily log return of a given meme token. *All token index return* is the average daily log return of all meme token returns. *Meme style index return* is the average daily log return of all meme tokens with the same meme style. *Similar-code index return* is the average daily log return of all meme tokens that have the similar source codes. We assume that source codes for two tokens are similar if there Jaccard index is greater than 0.99. We report coefficient estimates and their t-statistics. Standard errors are clustered by day. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Token return				
	(1)	(2)	(3)	(4)	(5)
All token index return	0.543***	0.478***			
	(64.07)	(48.49)			
Meme style index return		0.106***	0.101***	0.033***	0.034***
		(22.84)	(6.83)	(4.03)	(4.03)
Similar-code index return					0.141***
					(10.28)
Day FE	No	No	Yes	Yes	Yes
N	1,412,705	1,303,560	1,303,560	339,600	339,600
Adjusted R^2	0.0023	0.0030	0.0102	0.0046	0.0080

Table 3. Past return and token issuance, trading volume and creator's profit

In this table, we report the relationship between past meme style index return and future token issuance, trading volume, and creator's profit. *Log(# tokens issued at t+1)* is the logarithm of one plus the number of tokens issued next day for a given meme style. *Log(trading volume at t+1)* is the logarithm of next day trading volume for a given meme style. *Log(creator's profit at t+1)* is the logarithm of creators' profit on next day for a given meme style. *Meme style index return in [t-14,t]* is the return on the meme style index over the last 14 days. *Log(# tokens issued in [t-14,t])* is the logarithm of one plus the number of tokens issued over the last 14 days for a given meme style. *Log(trading volume in [t-14,t])* is the logarithm of trading volume of all tokens in a given meme style over the last 14 days. We report coefficient estimates and their *t*-statistics. Standard errors are clustered at the meme style and day level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log(# tokens issued at t+1)		Log(trading volume at t+1)		Log(creator's profit at t+1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Meme style index return	0.045***	0.031***	0.159***	0.130***	0.056***	0.033***
in [t-14, t]	(4.41)	(4.65)	(7.96)	(7.68)	(4.94)	(3.90)
Log(# tokens issued in	0.048***	0.020***	0.822***	0.672***	0.081***	0.046***
[t-14, t])	(6.20)	(3.78)	(52.44)	(35.16)	(7.67)	(6.86)
Log(trading volume in	0.493***	0.361***	0.094***	0.099***	0.373***	0.324***
[t-14,t])	(26.00)	(14.18)	(4.56)	(2.79)	(16.29)	(13.61)
Meme style FE	No	Yes	No	Yes	No	Yes
Day FE	No	Yes	No	Yes	No	Yes
N	47,882	47,879	47,882	47,879	47,882	47,879
Adjusted R^2	0.6541	0.7331	0.6963	0.7438	0.3065	0.3665

Table 4. Token level regression

In this table, we show the relationship between past meme style index return and trading volume and creator's profit of newly issued tokens. *Log(trading volume for the first 30 days)* is the logarithm of total trading volume of a given token for the first 30 days after issuance. *Log(creator's profit for the first 30 days)* is the logarithm of creator's profit of a given token for the first 30 days after issuance. *Meme style index return in [t-14, t]* is the return on the meme style index over the last 14 days. *Log(# tokens issued in [t-14,t])* is the logarithm of one plus the number of tokens issued over the last 14 days for a given meme style. *Log(trading volume in [t-14,t])* is the logarithm of trading volume of all tokens in a given meme style over the last 14 days. We report coefficient estimates and their *t*-statistics. Standard errors are clustered at the meme style and day level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log(trading volume for the first 30 days)			Log(creator's profit for the first 30 days)		
	(1)	(2)	(3)	(4)	(5)	(6)
Meme style index return	-0.060	-0.033	0.001	0.022*	-0.008	-0.011
in [t-14, t]	(-1.33)	(-1.60)	(0.05)	(1.70)	(-0.67)	(-0.73)
Log(trading volume in	0.102***	0.118***	0.081***	0.032***	0.056***	0.033***
[t-14,t])	(3.13)	(5.57)	(4.78)	(3.48)	(5.36)	(2.84)
Meme FE	No	Yes	Yes	No	Yes	Yes
Day FE	No	Yes	Yes	No	Yes	Yes
Control variables	No	No	Yes	No	No	Yes
Observations	268,243	268,221	154,213	268,243	268,221	154,213
Adjusted R2	0.0062	0.0865	0.0738	0.0014	0.0236	0.0376

Table 5. Past return and rug pulls and rug pull profit

In this table, we report the relationship between past meme style index return and number of new rug pulls, and rug pull profit. *Log(# rug pulls at t+1)* is the logarithm of one plus the number of rug pulls occurred next day. *Log(rug pull profit at t+1)* is the logarithm of the total rug pull profit of all rug pulls occurred next day. The other variables are defined in Table 3. We report coefficient estimates and their *t*-statistics. Standard errors are clustered by the meme style and day level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log(# rug pulls at t+1)		Log(rug pull profit at t+1)	
	(1)	(2)	(3)	(4)
Meme style index return in [t-14, t]	0.041***	0.032***	0.120***	0.081***
	(3.82)	(4.93)	(5.24)	(4.87)
Log(# tokens issued in [t-14, t])	0.031***	0.009	0.105***	0.028*
	(3.88)	(1.62)	(6.80)	(1.81)
Log(trading volume in [t-14,t])	0.422***	0.332***	1.291***	0.974***
	(20.37)	(13.13)	(41.49)	(19.11)
Meme style FE	No	Yes	No	Yes
Day FE	No	Yes	No	Yes
N	47,882	47,879	47,882	47,879
Adjusted R2	0.5891	0.6937	0.4859	0.5446

Table 6. Determinants of participation in meme-token trading

In this table, we explore determinants of participation in meme token trading. *Participate in meme-token trading* is a dummy that equals 1 if an investor trades meme tokens in month *t+1* and 0 otherwise. The independent variables are investor characteristics measured at the end of month *t*. *Log(Price)* is the natural logarithm of the median price (in Binance Coin) across all the previous purchases up until *t*. *Selling probability* is the daily probability of selling a held cryptocurrency. *Log(Portfolio size)* is the natural logarithm of the portfolio size (in Binance Coin) at the end of month *t*. *Experience* is the number of years since an investor started to trade on PancakeSwap. *Investor return$_t$* is portfolio returns in month *t*. We report coefficient estimates and their *t*-statistics. Standard errors are clustered by investor and year-month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Summary statistics

	Mean	1st quartile	Median	3rd quartile	Std. Dev.
Participation (%)	0.169	0	0	0	0.375
Log (Price, in Binance Coin)	-11.210	-18.862	-6.761	-4.862	8.681
Selling probability	0.026	0.002	0.011	0.030	0.049
Log (Portfolio size, in Binance Coin)	4.201	1.957	3.143	5.005	6.177
Experience (years)	0.259	0.133	0.225	0.367	0.150
Investor return	0.230	-0.204	-0.060	0.178	1.850

Panel B. Participation in meme-token trading

	Participate in meme-token trading					
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Price)	-0.006***					-0.007**
	(-5.59)					(-6.67)
Selling probability		0.795***				1.148***
		(5.88)				(8.61)
Log(Portfolio size)			0.005***			0.006***
			(4.71)			(5.61)
Experience (years)				-0.060**		-0.067**
				(-2.22)		(-4.94)
Investor return					0.020***	-0.001
					(9.13)	(-0.29)
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	46,348,917	46,348,917	46,348,917	46,064,266	46,348,917	46,064,266
Adjusted R2	0.0470	0.0347	0.0321	0.0254	0.0245	0.0783

Appendix

I. Decentralized Exchanges

In this section of Appendix, we provide further description of decentralized exchanges.

I.1. Comparison with other major DEXs

In this subsection, we compare features of PancakeSwap with those of four other major DEXs. As of October 2021, the five DEXs commanded a combined market share of about 65% among all DEXs (CoinMarketCap, 2021). Ethereum-based Uniswap is a major DEX competitor of PancakeSwap. Although Uniswap is one of the earliest DEX in the marketplace, its growth has slowed since 2020, largely due to slow transaction speed and high gas costs caused by Ethereum's scalability issues. Uniswap's (version 2) trading volume was surpassed by PancakeSwap on February 19, 2021.[19] Unlike PancakeSwap, Uniswap does not offer yield farming options or other functions. The only way to earn yields is to collect trading fees from LP tokens.

SushiSwap is a multi-chain AMM that currently supports 14 major blockchains, including Ethereum, BSC, and Polygon. It was originally built on Ethereum but to escape Ethereum gas fees in early March 2021 it decided to go live on multiple blockchains. Similar to PancakeSwap, the platform offers yield farming (staking the native SUSHI token for xSUSHI) and crypto lending, which PancakeSwap does not provide.

The 1inch Network is essentially a DEX exchange aggregator. It scrapes other exchanges to provide users with the cheapest prices, routing trades to the exchanges that offer the best prices and lowest fees. 1inch connects to dozens of major DEXs, including

[19] UniSwap V3, launched on May 5, 2021, rolled out a "layer 2" scaling solution upgrade, which is designed to help scale DApps by handling transactions off the Ethereum Mainnet (layer 1). This upgrade has reduced trading costs and increased speed significantly.

PancakeSwap, Uniswap, SushiSwap, and 1inch's own AMM, the 1inch Liquidity Protocol (formerly known as Mooniswap). In addition to DEXs, it also integrates several other DeFi protocols, including yield farming platform Aave.

dYdX is an Ethereum-based DEX that offers margin trading (e.g., up to 25 times for ETH-USD pair) and derivatives. It also provides the ability for traders to make fully-collateralized loans, which are used to fund short selling.

I.2. Comparison with centralized exchanges (CEXs)

In this subsection, we compare DEXs such as PancakeSwap with CEXs along several major dimensions.

Custodial trading and security issues

Transactions on CEXs are kept off-chain and are not recorded on the blockchain. CEXs take custody of traders' funds, which are consolidated into several high-value wallets controlled by the exchanges. This makes them a lucrative target for hackers, who steal user information, funds, and private keys. CEXs have proven to be vulnerable to hacks, losing $2.8 billion worth of customer funds between 2011 and 2020 (Crystal Blockchain, 2020). As most CEXs are not insured by banking regulators, customers have little recourse in cases of theft. For a permissionless DEX such as PancakeSwap, customer funds are in their own custody, thus eliminating the security issues that plague CEXs.

Fees

Although depositing cryptos from a private wallet into a CEX wallet is generally free, CEXs often charge a withdrawal fee. For example, Binance currently takes the cryptocurrency equivalent of $1 to $15. Users are also subject to blockchain network/gas fees when they deposit or withdraw cryptos. In addition, CEXs also charge a trading fee, ranging from 0.1% to 0.5% of the value of each trade for both the buyer and the seller. To trade on a DEX, users do not need to deposit or withdraw funds. The only trading cost they incur is the network fee.

The availability of currency pairs

CEXs generally feature only the most popular currency pairs. For instance, as of October 2021, Coinbase offered only over 300 pairs while Binance US offered 120. However, DEXs typically offer thousands of trading pairs because liquidity suppliers can create any liquidity pool on a DEX with little cost to facilitate trading of any currency pair. Therefore, for smaller tokens, including meme tokens, DEXs are often the only trading venues available. In addition, in countries where cryptocurrency trading is banned, traders cannot access CEXs but potentially rely on DEXs.

KYC requirement and fraud

Most established CEXs implement a Know Your Customer (KYC) process that verify users' identify, which helps create a more trusted and secure trading environment. However, DEXs such as PancakeSwap are under no regulatory authority for such a process. Any user in the world can create a liquidity pool and any trader is able to trade against the liquidity pool. Because of the lack of KYC, fraudulent behavior, such as rug pulls, takes place regularly. In a rug pull, malicious individuals create a token, list it on a DEX, and pair it with a leading cryptocurrency such as WBNB. Once a significant number of unsuspecting investors swap their WBNB for the listed token, the creators then withdraw all liquidity from the liquidity pool, driving the token's price to zero. The token creators often create hype on Telegram, Twitter, and other social media platforms and initially inject plenty of liquidity into their pool to attract potential investors.[20]

II. An Example of Automated Market Makers (AMMs)

Each token swap a trader initiates on an AMM results in a price adjustment according to a deterministic pricing algorithm. Many protocols, including PancakeSwap, use a constant product algorithm that makes sure that the product of the quantities of the two supplied tokens remains the same. This relationship is sometimes referred to as a bonding curve. To illustrate the mechanisms of the AMM, below we provide an example regarding the ETH-BNB pair.

We assume that a sole LP provides 100 ETH and 1,000 BNB tokens to a PancakeSwap liquidity pool (assuming the fair exchange rate is 1:10) and she receives 1,000 liquidity tokens. Thus the constant product $k = 100 \times 1{,}000 = 100{,}000$. Assume that a trader swaps 100 BNB for ETH. Given that PancakeSwap charges a fee of 0.25%, the effective amount of BNB that is traded is 99.75. The total number of BNB before the fee revenue is added to the pool increases to 1,099.75. According to the bonding curve, the new balance of ETH in the pool equals 90.9298 (100,000/1,099.75). Therefore, the trader

[20] Flash loan attacks are another type of DeFi fraud where an individual takes out a flash loan (a form of uncollateralized loan) from a crypto lending protocol and uses it to manipulate the market in their favor. The reader is referred to https://coinmarketcap.com/alexandria/article/what-are-flash-loan-attacks for details.

receives 9.0702 ETH. The effective exchange rate for the trader is 9.0702/100 = 0.91:10. This swap transaction increases the relative price of ETH.

As PancakeSwap specifies, LP token holders receive a fee of 0.17%, with the remaining 0.08% being kept in the PancakeSwap Treasury to maintain the platform. Therefore, the total BNB balance in the pool post-trade equals (1,099.75 + 0.17) = 1,099.92. The new constant product becomes 100,015.50 (90.9298 $\times$ 1,099.92), which will be applied to the next trade. When the LP redeems all her LP tokens, she receives 90.9298 ETH and 1,099.92 BNB.

While still earning the 0.17% trading fee reward, users can deposit or "stake" their LP tokens on PancakeSwap's "yield farms" to earn CAKE tokens, PancakeSwap's native token (See Augustin, Chen-Zhang, and Shin (2022) for details on yield farming). In addition, users can stake CAKE tokens in the "Syrup Pools" in return for tokens belonging to other BSC projects. Other than yield farming, Pancakeswap also provides a lottery, an NFT market, and initial farm offerings in which users buy new tokens using CAKE-BNB LP tokens, all of which we don't discuss in detail in this paper.

III. Rug Pulls

To define rug pull profit, we should take into account potential trading by liquidity providers and their collaborators. In order to attract the outside investors to buy the tokens, it is plausible that the liquidity provider buys the tokens to generate an increasing pattern of token price. Not only that, the liquidity provider can collaborate a group of other wallets by letting them to buy the tokens to create the artificial price increase. Such manipulative trading practice appears similar to 'crypto wash trading' commonly observed in centralized cryptocurrency exchanges (Aloosh and Li, 2021; Amiram, Lyandres, and Rabetti, 2021;

Cong, Li, Tang, and Yang, 2021). However, this manipulative practice is different from 'crypto wash trading' in the sense that all the collaborators involve in this trading not only to increase the trading volume but also significantly increase the price. In order not to overestimate the rug pull profit, we first identify all the people who have withdrawn liquidity from each liquidity pool. Then we track the pattern of transfer of BNBs between the creators, liquidity withdrawers, and other wallets. If the BNBs are transferred not through executions of any smart contracts, we consider that wallets are connected. Once we identify the collaborators of the creator and liquidity withdrawer, we define rug pull profit is the net BNB amount from liquidity provision and withdrawal activities minus the net inflow of BNBs of all the collaborators' trading activities.

In addition, it is possible that liquidity can be withdrawn fast for a token even though it is not a rug pull. For example, if a creator makes a token to test validity of a source code for a token, the creator can quickly remove the liquidity after initial liquidity provision, in which case the profit is close to $0. Therefore, we should identify tokens for which the profit is economically significant.

Taken together, we define that a token is a rug pull if this token satisfies the following conditions: (1) τ is less than or equal to 5 days. (2) The value of the rug pull profit is greater than $50, which is economically significant. For robustness of the results, we also provide additional results using different threshold. (3) The size of a liquidity pool decreases more than 90% after the liquidity withdrawal.

Example of a rug pull (LAMBO token)

On June 30, 2021, LAMBO token was announced in its own subreddit page.[21] The announcement describes the LAMBO token as follows, *"Probably everyone would like to*

[21] https://www.reddit.com/r/LAMBOCommunity/comments/oaufdt/lambo_token/

make money on a new Lambo thanks to the crypt. And you will be able to do it! $LAMBO is the next evolution of a yield-generating contract on the Binance Smart Chain (BSC): you get rewarded in BNB instead of tokens." (See Figure 4 Panel A.) Unlike a whitepaper of a typical ICO which describes the business ideas and utility of issued tokens, the announcement is silent about them but rather focuses only on a high potential investment return. The token was scheduled to be launched at 06:00:00 PM on July 3, 2021 in GMT.

LAMBO token (token address: 0x6ad62bdb4b5ac758da8ffce938904378c970be2f) was created by a creator whose wallet address is 0xbfe19bde340af1b326f5f6509a304d09cc52f93d at 04:59:17 PM on July 3, 2021 in GMT. The total supply was 777,000,000,000 LAMBOs. After about an hour at 05:57:10 PM, the creator provided initial liquidity amounting to 300 BNBs and 738,150,000,000 LAMBOs to a liquidity pool in PancakeSwap v2 and received 14,881,028.19 LAMBO-BNB LP tokens. The first token purchase was made at 05:57:13 PM by 0x1bca18e8034f2dd789ce161bd7e30429d581cd16 which is about 3 minutes before the scheduled launch time. Since the initial liquidity provision, many other outside investors aggressively purchased this token, which created a dramatic increase in price as shown in Figure 4 Panel B. The price increased to $4.54 * 10^{-8}$ BNB from its initial price $4.06*10^{-10}$ BNB within first 30 minutes, meaning the rate of return of 11,078.07%.

At 06:31:34 PM, the creator suddenly withdrew all liquidity by sending back all 14,881,028.19 LAMBO-BNB LP tokens to PancakeSwap. Through the liquidity withdrawal in a short time, called a rug pull, the creator received 69,936,426,516.9 LAMBOs and 3,179.08 BNBs. Overall, within about 35 minutes, the creator earned 2879.08 BNBs equivalent to $858,656.8. A reply to a reddit post suggests that the creator of the tokens deleted the Twitter page and website of LAMBO token and stopped communicating in Telegram immediately after the rug pull on July 3, 2021.[22]

Interestingly, between the initial liquidity provision and the withdrawal of liquidity, we only observe buy orders without even a single sell order. This is because this token was a honey pot, meaning investors can only buy and cannot sell the token by its design. A later post written by RoyalKend at 08:43:16 PM and replies to this post suggest that a vast majority of investors did not recognize the honey pot property of this token when they initially bought the tokens.[23] In the end, such an exploitative attempt generated complaints from investors as shown in an announcement in the subreddit page highlighting that LAMBO tokens is a rug pull (Figure 4 Panel C).

Prevalence of rug pulls

In order to check the validity of our method to identify scams, we manually check the 'comments' tab of large rug pull tokens in BscScan where investors freely share their opinions about the tokens. Although not all scams are reported in the comment tab, we guess that investors could be likely report the scam tokens if the size of the scam is large, which leads to focus on the 20 largest rug pulls. Among 20 largest rug pulls, we find that there are scam accusations for 19 tokens among 20 rug pull tokens. While this may not be conclusive, the result is reassuring that our methodology detects rug pulls reliably.

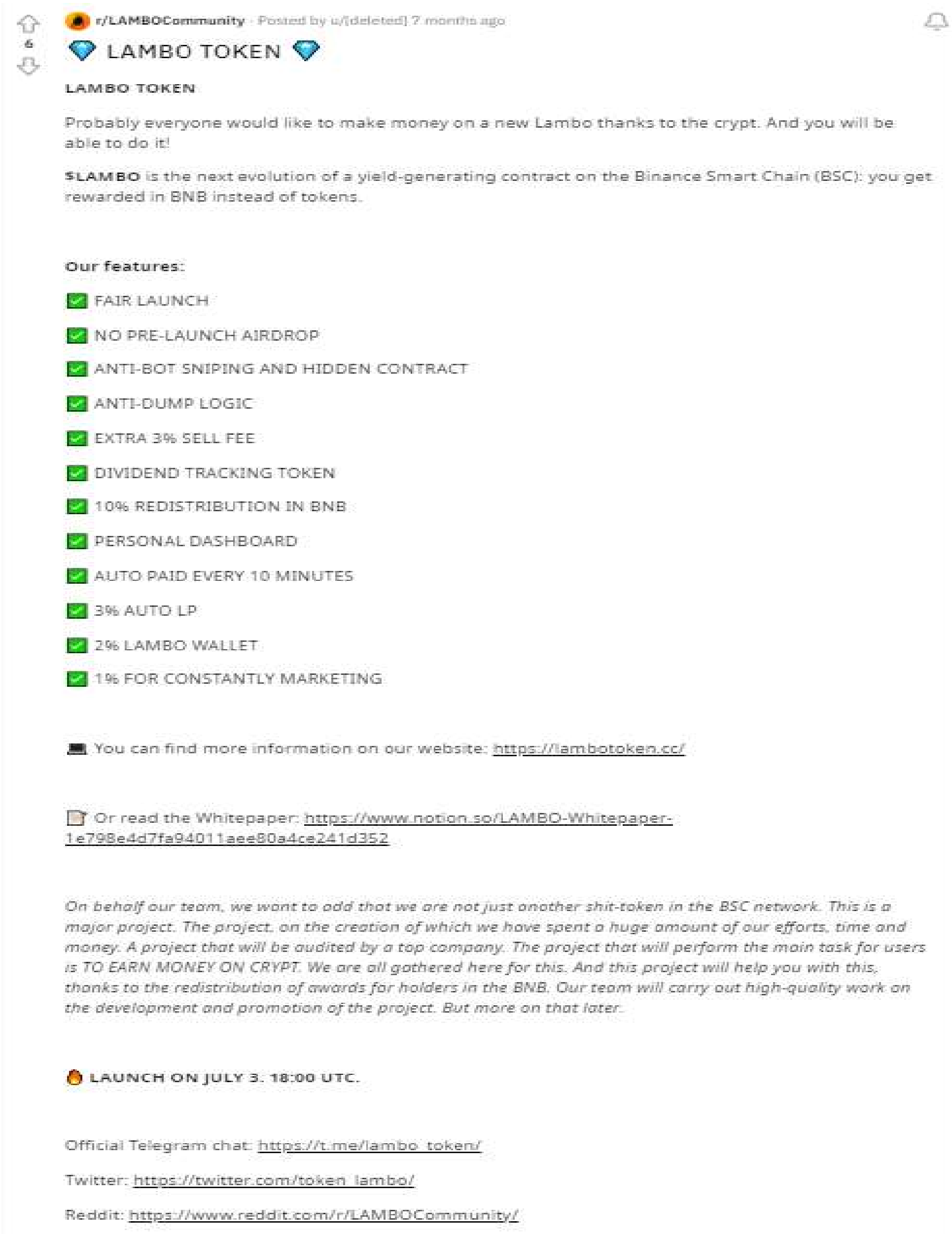
[22] https://www.reddit.com/r/LAMBOCommunity/comments/od3tk2/is_lambo_a_honeypot_or_will_we_be_able_to_sell_it/h3y4o6o/?utm_source=reddit&utm_medium=web2x&context=3
A user, vikings101, wrote at 09:06:32 PM on July 3, 2021: "*For anyone holding out hope - the website is gone, twitter page is gone, reddit user that created all the posts is gone, and telegram has stopped communication*"
[23] https://www.reddit.com/r/LAMBOCommunity/comments/od3tk2/is_lambo_a_honeypot_or_will_we_be_able_to_sell_it/

The size of rug pulls is large and they are pervasive in the cryptocurrency market. Figure A2 plots aggregate rug pull profit depending on the timing of the withdrawal of the liquidity. The figure shows that the aggregate rug pull profit. We find that total rug pull profit in our sample period is $249.63M with 354,199 rug pulls. The number of rug pulls changes depending on whether we use $50 or $100 as a minimum rug pull profit threshold. However, the total rug pull profit only marginally changes. ($247.12M if the threshold is $50.)

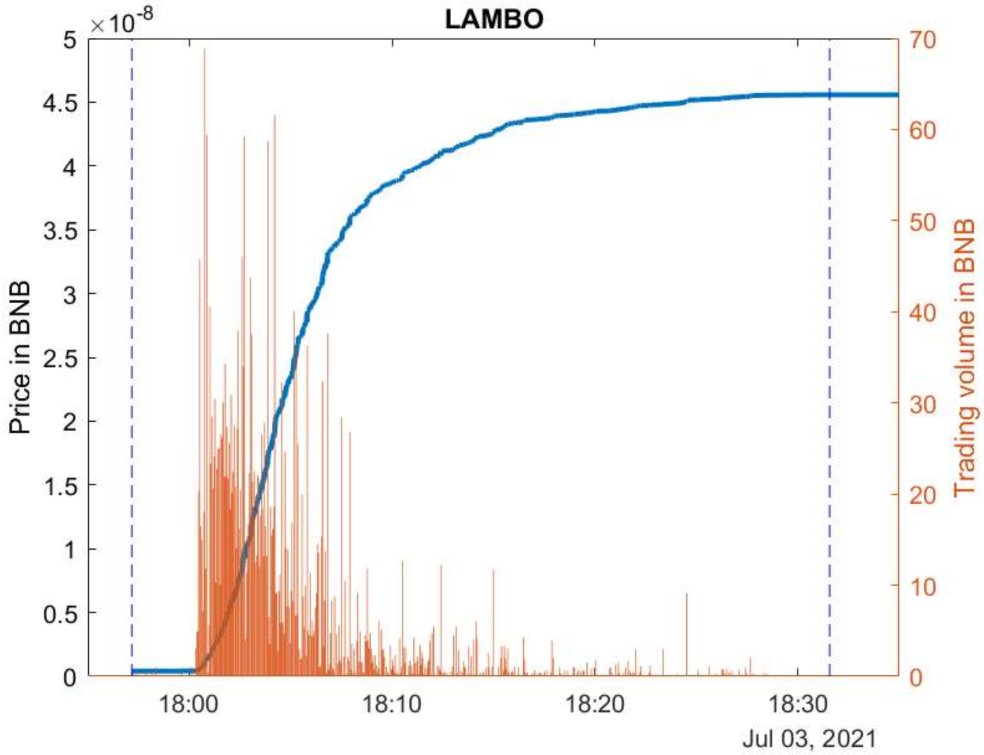
Figure A1. A rug pull example (LAMBO token)

In this figure, we give an example of a rug pull, LAMBO token. In Panel A, we provide a snapshot of Reddit announcement of LAMBO token. In Panel B, we plot price and trading volume of LAMBO token on July 3, 2021. The blue line plots price of LAMBO token in BNB unit and the red bar plots trading volume in BNB unit. The two dashed vertical lines indicate the timings of initial liquidity provision and withdrawal of liquidity by the creator. Panel C presents a snapshot of subreddit page announcing that LAMBO token turns out to be a rug pull.

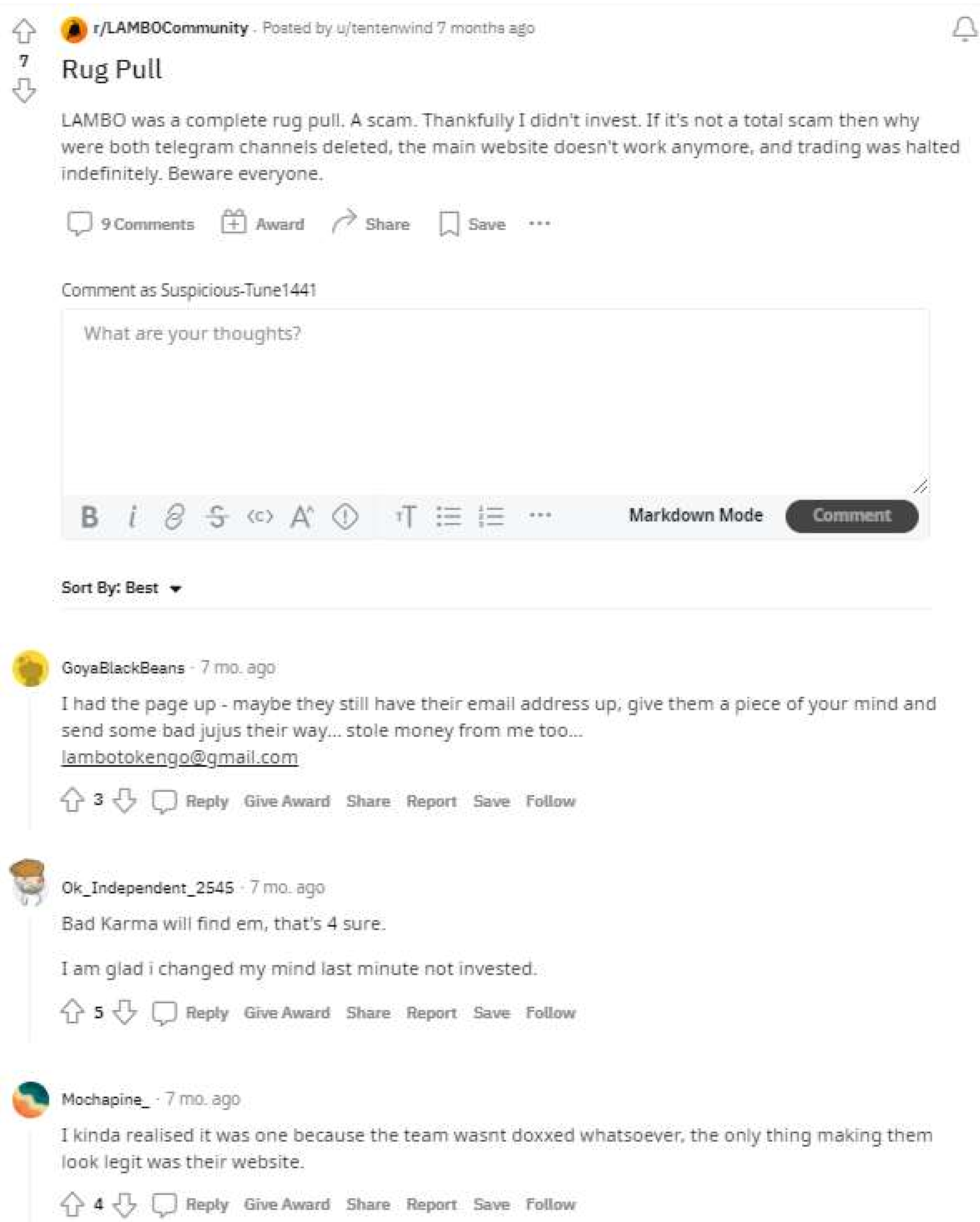
Panel A. Reddit announcement



Panel B. Price and trading volume of LAMBO token



Panel C. Rug pull announcement



r/LAMBOCommunity · Posted by u/tentenwind 7 months ago

7

Rug Pull

LAMBO was a complete rug pull. A scam. Thankfully I didn't invest. If it's not a total scam then why were both telegram channels deleted, the main website doesn't work anymore, and trading was halted indefinitely. Beware everyone.

9 Comments Award Share Save ···

Comment as Suspicious-Tune1441

What are your thoughts?

Markdown Mode Comment

Sort By: Best

GoyaBlackBeans · 7 mo. ago

I had the page up - maybe they still have their email address up, give them a piece of your mind and send some bad jujus their way... stole money from me too...
lambotokengo@gmail.com

3 Reply Give Award Share Report Save Follow

Ok_Independent_2545 · 7 mo. ago

Bad Karma will find em, that's 4 sure.

I am glad i changed my mind last minute not invested.

5 Reply Give Award Share Report Save Follow

Mochapine_ · 7 mo. ago

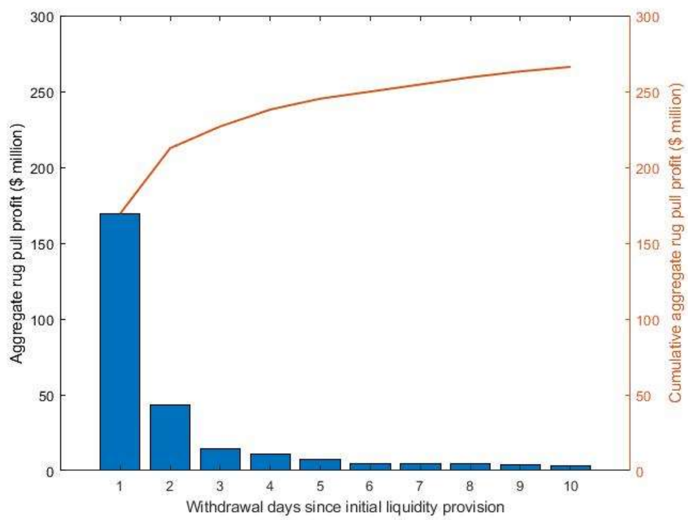
I kinda realised it was one because the team wasnt doxxed whatsoever, the only thing making them look legit was their website.

4 Reply Give Award Share Report Save Follow

Figure A2. Rug pull profit

In Panel A, we plot aggregate rug pull profit depending on the days elapsed from the first liquidity provision of a creator until the creator withdraws more than 99% of provided liquidity. The blue bar plots the aggregate rug pull profit per each duration in days. The red line plots the cumulative aggregate rug pull profit. In Panel B, we plot monthly aggregate rug pull profit with the blue bar and the number of rug pulls with the red line. The sample period is from September 2020 to December 2021.

Panel A



Panel B

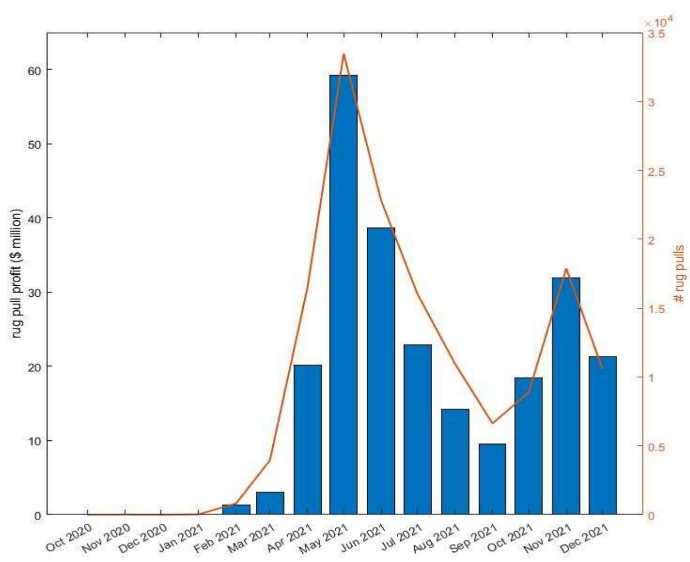


Figure A3. Similar Token Example

We illustrate examples of similar token pairs that we identified using the Jaccard similarity index. Below are the source codes of two tokens: Blimp Protocol[24] and Baby Shiba Army[25]. We compute that the Jaccard similarity between Blimp Protocol and Baby Shiba Army is 99.75%. By comparing the source codes of them, we find that among over 900 lines of code, only one line is different as highlighted below.[26]

```
interface IERC20 {

    function totalSupply() external view returns (uint256);
    function balanceOf(address account) external view returns (uint256);
    function transfer(address recipient, uint256 amount) external returns (bool);
    function allowance(address owner, address spender) external view returns (uint256);
    function approve(address spender, uint256 amount) external returns (bool);
    function transferFrom(address sender, address recipient, uint256 amount) external returns (bool);

    event Transfer(address indexed from, address indexed to, uint256 value);
    event Approval(address indexed owner, address indexed spender, uint256 value);
}

library SafeMath {

    function tryAdd(uint256 a, uint256 b) internal pure returns (bool, uint256) {
        unchecked {
            uint256 c = a + b;
            if (c < a) return (false, 0);
            return (true, c);
        }
    }

    function trySub(uint256 a, uint256 b) internal pure returns (bool, uint256) {
        unchecked {
            if (b > a) return (false, 0);
            return (true, a - b);
        }
    }

     function swapExactTokensForETHSupportingFeeOnTransferTokens(
        uint amountIn,
        uint amountOutMin,
        address[] calldata path,
        address to,
        uint deadline
    ) external;
}

contract BlimpProtocol is Context, IERC20, Ownable {
    using SafeMath for uint256;
    using Address for address;

    mapping (address => uint256) private _rOwned;
    mapping (address => uint256) private _tOwned;
    mapping (address => mapping (address => uint256)) private _allowances;
    mapping (address => bool) private _isExcludedFromFee;
    mapping (address => bool) private _isExcluded;
    address[] private _excluded;
     function _transferFromExcluded(address sender, address recipient, uint256 tAmount) private {
        (uint256 rAmount, uint256 rTransferAmount, uint256 rFee, uint256 tTransferAmount, uint256 tFee, uint256 tLiquidity, uint256 tDev) = _getValues(tAmount);
        _tOwned[sender] = _tOwned[sender].sub(tAmount);
        _rOwned[sender] = _rOwned[sender].sub(rAmount);
        _rOwned[recipient] = _rOwned[recipient].add(rTransferAmount);
        _takeLiquidity(tLiquidity);
        _takeDev(tDev);
        _reflectFee(rFee, tFee);
        emit Transfer(sender, recipient, tTransferAmount);
    }


    function setRouterAddress(address newRouter) external onlyOwner {
        IUniswapV2Router02 _uniswapV2Router = IUniswapV2Router02(newRouter);
        uniswapV2Pair = IUniswapV2Factory(_uniswapV2Router.factory()).createPair(address(this), _uniswapV2Router.WETH());
        uniswapV2Router = _uniswapV2Router;
    }

    function setNumTokensSellToAddToLiquidity(uint256 amountToUpdate) external onlyOwner {
        numTokensSellToAddToLiquidity = amountToUpdate;
    }



}
```

```
interface IERC20 {

    function totalSupply() external view returns (uint256);
    function balanceOf(address account) external view returns (uint256);
    function transfer(address recipient, uint256 amount) external returns (bool);
    function allowance(address owner, address spender) external view returns (uint256);
    function approve(address spender, uint256 amount) external returns (bool);
    function transferFrom(address sender, address recipient, uint256 amount) external returns (bool);

    event Transfer(address indexed from, address indexed to, uint256 value);
    event Approval(address indexed owner, address indexed spender, uint256 value);
}

library SafeMath {

    function tryAdd(uint256 a, uint256 b) internal pure returns (bool, uint256) {
        unchecked {
            uint256 c = a + b;
            if (c < a) return (false, 0);
            return (true, c);
        }
    }

    function trySub(uint256 a, uint256 b) internal pure returns (bool, uint256) {
        unchecked {
            if (b > a) return (false, 0);
            return (true, a - b);
        }
    }

     function swapExactTokensForETHSupportingFeeOnTransferTokens(
        uint amountIn,
        uint amountOutMin,
        address[] calldata path,
        address to,
        uint deadline
    ) external;
}

contract CoinToken is Context, IERC20, Ownable {
    using SafeMath for uint256;
    using Address for address;

    mapping (address => uint256) private _rOwned;
    mapping (address => uint256) private _tOwned;
    mapping (address => mapping (address => uint256)) private _allowances;
    mapping (address => bool) private _isExcludedFromFee;
    mapping (address => bool) private _isExcluded;
    address[] private _excluded;
     function _transferFromExcluded(address sender, address recipient, uint256 tAmount) private {
        (uint256 rAmount, uint256 rTransferAmount, uint256 rFee, uint256 tTransferAmount, uint256 tFee, uint256 tLiquidity, uint256 tDev) = _getValues(tAmount);
        _tOwned[sender] = _tOwned[sender].sub(tAmount);
        _rOwned[sender] = _rOwned[sender].sub(rAmount);
        _rOwned[recipient] = _rOwned[recipient].add(rTransferAmount);
        _takeLiquidity(tLiquidity);
        _takeDev(tDev);
        _reflectFee(rFee, tFee);
        emit Transfer(sender, recipient, tTransferAmount);
    }


    function setRouterAddress(address newRouter) external onlyOwner {
        IUniswapV2Router02 _uniswapV2Router = IUniswapV2Router02(newRouter);
        uniswapV2Pair = IUniswapV2Factory(_uniswapV2Router.factory()).createPair(address(this), _uniswapV2Router.WETH());
        uniswapV2Router = _uniswapV2Router;
    }

    function setNumTokensSellToAddToLiquidity(uint256 amountToUpdate) external onlyOwner {
        numTokensSellToAddToLiquidity = amountToUpdate;
    }



}
```

[24] 0xa30E7A918c590BfF2d102E7F4cBaaa1122350Efe

[25] 0xb74fcfF27a8113bA6f1Ba613D0Be776C2A956180

[26] The complete source code comparison is accessible here: https://bscscan.com/contractdiffchecker?a2=0xb74fcff27a8113ba6f1ba613d0be776c2a956180&a1=0xa30e7a918c590bff2d102e7f4cbaaa1122350efe

Figure A4. Competition for Attention – number of meme keywords

In this figure, we plot fraction of meme tokens that have one, two, and three meme keywords in their names. The blue, red, and yellow lines plots the fraction of tokens that have one, two, and three meme keywords, respectively.

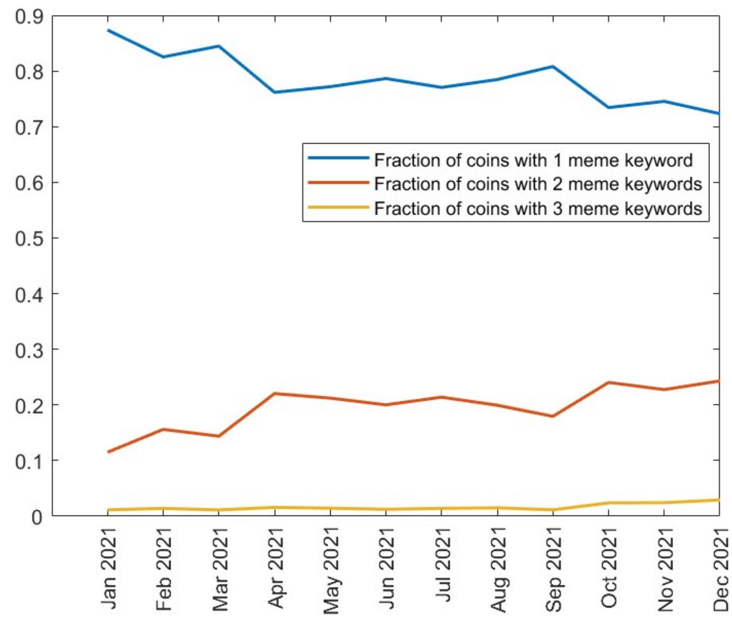


Table A1: Summary Statistics on Rug Pulls

This table presents summary statistics for rug pull profit. Rug pull profit is net profit of insiders in a rug pull. For each variable, we define rug pull in two different manners. Rug pull is a rug pull whose rug pull profit is positive. Rug pull (> \$50 profit) is a rug pull whose rug pull profit is greater than \$50.

	Total (\$M)	Average (\$)	Q1 (\$)	Median (\$)	Q3 (\$)	SD (\$)	N
Rug pull profit							
Rug pull	249.63	704.80	5.14	29.72	163.36	7,497.29	354,199
Rug pull (>\$50 profit)	247.12	1,658.77	100.55	231.61	787.20	11,492.07	148,979

Table A2. Predicting Rug Pulls

This table presents the rug pull detection results using a linear probability model. The dependent variables are a dummy variable indicating whether a token is a rug pull, a dummy variable whether the rug pull profit is greater than $50, and logarithm of 1 + rug pull profit. *Is meme token* is a dummy equal to 1 if the name of the token contains meme-related keywords. Other independent variables are described in Table 1. The standard errors are clustered at creator and year-month level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Rug Pull		Rug pull (>$50)		Rug pull profit	
	(1)	(2)	(3)	(4)	(5)	(6)
# tokens issued by same creator before	-0.0747***	-0.0889***	-0.0648***	-0.0726***	-0.450***	-0.492***
	(-12.07)	(-11.76)	(-8.34)	(-8.93)	(-9.81)	(-10.12)
Rug pull profit made by the creator before	0.0945***	0.0771***	0.0504***	0.0369***	0.411***	0.310***
	(50.61)	(22.46)	(14.88)	(11.98)	(27.92)	(25.78)
# rug pulls in the same cluster before	-0.0434***	-0.0431***	-0.0906***	-0.0891***	-0.503***	-0.491***
	(-8.31)	(-9.03)	(-19.27)	(-19.13)	(-21.25)	(-19.73)
Rug pull profit in the same cluster before	0.0554***	0.0691***	0.0659***	0.0711***	0.405***	0.448***
	(12.26)	(19.20)	(21.52)	(25.25)	(18.58)	(22.22)
Is meme token	0.0260***	0.00175	0.0462***	0.0218***	0.238***	0.0677***
	(4.20)	(0.29)	(12.10)	(6.80)	(9.26)	(4.51)
Length of the token source code		-0.0370***		0.00787		-0.0655
		(-3.18)		(0.71)		(-1.01)
No. of similar tokens (99%)		-0.0393***		-0.0190***		-0.143***
		(-17.36)		(-15.26)		(-28.22)
% Token retained by creator		-0.135***		-0.146***		-0.970***
		(-9.62)		(-14.60)		(-14.68)
% LP token burned		-0.269***		-0.0864**		-0.857***
		(-4.72)		(-2.19)		(-3.20)
Token initial price		-0.00404		-0.00641***		-0.0499***
		(-1.69)		(-5.90)		(-9.92)
Constant	0.414***	0.869***	0.175***	0.191	1.516***	2.735***
	(12.74)	(6.05)	(11.01)	(1.65)	(12.10)	(3.71)
N	584,426	333,328	584,426	333,328	584,426	333,328
Adjusted R2	0.446	0.486	0.178	0.188	0.330	0.349

Table A3. Token performance of tokens with identical names

In this table, we study the performance of tokens with identical names. *Log(trading volume for the first 30 days)* is the logarithm of total trading volume of a given token for the first 30 days after issuance. *Log(creator's profit for the first 30 days)* is the logarithm of creator's profit of a given token for the first 30 days after issuance. *Identical name* is a dummy equal to 1 if the name of a given token is the same as the name of the token with highest trading volume in a given meme style, and 0 otherwise. *Meme style index return in [t-14,t]* is the return on the meme style index over the last 14 days. *Log(trading volume in [t-14,t])* is the logarithm of trading volume of all tokens in a given meme style over the last 14 days. We report coefficient estimates and their *t*-statistics. Standard errors are clustered at the meme style and day level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log(trading volume in the first 30 days)		Log(creator's profit in the first 30 days)	
	(1)	(2)	(3)	(4)
Identical name	-1.073***	-1.137***	-0.462**	-0.439*
	(-2.97)	(-3.22)	(-2.07)	(-1.99)
Meme style index return in [t-14, t]	-0.023		0.001	
	(-0.85)		(0.02)	
Log(trading volume in [t-14,t])	0.015		0.028*	
	(0.67)		(1.98)	
Meme style FE	Yes	No	Yes	No
Day FE	Yes	No	Yes	No
Meme style x Day FE	No	Yes	No	Yes
Observations	214,499	214,153	214,499	214,153
Adjusted R-squared	0.2578	0.2742	0.0849	0.0968

Table A4. Token return similarity based on top 200 meme styles

In this table, we repeat Table 2 by focusing on top 200 meme styles based on the total trading volume of all tokens in each meme style. We report coefficient estimates and their *t*-statistics. Standard errors are clustered by day. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Token return				
	(1)	(2)	(3)	(4)	(5)
All token index return	0.540***	0.456***			
	(59.96)	(43.68)			
Meme style index return		0.113***	0.104***	0.024**	0.024**
		(20.56)	(5.67)	(2.56)	(2.57)
Similar-code index return					0.140***
					(9.56)
Day FE	No	No	Yes	Yes	Yes
N	1,271,178	1,235,557	1,235,557	323,683	323,683
Adjusted R-squared	0.0022	0.0028	0.0104	0.0045	0.0081

Table A5. Past return and token issuance, trading volume and creator's profit based only on newly issued tokens

In this table, we repeat Table 3 by using only newly issued tokens to compute the dependent variables. We report coefficient estimates and their t-statistics. Standard errors are clustered at the meme style and day level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log(# tokens issued at t+1)		Log(trading volume at t+1)		Log(creator's profit at t+1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Meme style index return in [t-14, t]	0.049***	0.030***	0.107***	0.063***	0.036***	0.015**
	(4.64)	(4.54)	(5.29)	(4.32)	(4.22)	(2.23)
Log(1+# tokens issued in [t-14, t])	-0.027***	-0.023***	0.101***	0.033***	0.023***	0.006
	(-4.42)	(-4.13)	(5.53)	(2.69)	(4.57)	(1.59)
Log(trading volume in [t-14,t])	0.579***	0.416***	0.662***	0.540***	0.152***	0.121***
	(19.64)	(12.93)	(12.22)	(10.48)	(8.68)	(5.74)
Meme style FE	No	Yes	No	Yes	No	Yes
Day FE	No	Yes	No	Yes	No	Yes
N	47,882	47,879	47,882	47,879	47,882	47,879
Adjusted R2	0.6499	0.7332	0.4374	0.5340	0.1304	0.1765

Table A6. Past return and token issuance, trading volume and creator's profit based on top 200 meme styles

In this table, we repeat Table 3 by focusing on top 200 meme styles based on the total trading volume of each meme style. We report coefficient estimates and their *t*-statistics. Standard errors are clustered at the meme style and day level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log(# tokens issued at t+1)		Log(trading volume at t+1)		Log(creator's profit at t+1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Meme style index return	0.040***	0.035***	0.151***	0.136***	0.053***	0.034***
in [t-14, t]	(3.23)	(4.38)	(6.02)	(6.64)	(3.98)	(3.20)
Log(1+# tokens issued	0.057***	0.029***	0.874***	0.748***	0.097***	0.054***
in [t-14, t])	(5.40)	(4.98)	(48.21)	(37.72)	(6.52)	(6.60)
Log(trading volume in	0.539***	0.425***	0.076***	0.093**	0.417***	0.376***
[t-14,t])	(26.01)	(15.02)	(3.74)	(2.29)	(16.89)	(13.65)
Meme style FE	No	Yes	No	Yes	No	Yes
Day FE	No	Yes	No	Yes	No	Yes
N	33,816	33,809	33,816	33,809	33,816	33,809
Adjusted R2	0.6774	0.7483	0.6896	0.7334	0.3105	0.3644

Table A7. Determinants of participation in meme-token trading

In this table, we repeat Table 5 by redefining the dependent variable. Unlike the dependent variable of Table 5, the new dependent variable, *Participate in meme-token trading,* is defined to be a dummy variable equal to 1 if an investor trades meme tokens that are not featured at CoinMarketcap and 0 otherwise. We report coefficient estimates and their *t*-statistics. Standard errors are clustered by investor and year-month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Participate in meme-token trading					
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Price)	-0.005***					-0.006***
	(-5.31)					(-6.55)
Selling probability		0.790***				1.131***
		(6.17)				(8.84)
Log(Portfolio size)			0.005***			0.006***
			(5.21)			(5.81)
Experience (year)				-0.042*		-0.046***
				(-1.89)		(-3.51)
Investor return					0.021***	-0.001
					(9.38)	(-0.20)
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	46,348,917	46,348,917	46,348,917	46,348,917	46,064,266	46,064,266
Adjusted R2	0.0382	0.0335	0.0313	0.0219	0.0236	0.0712