Beyond the Hype: Empirical Evaluation of Cryptocurrency Unicorn Success

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Abstract

Thousands of cryptocurrency coins and tokens have been introduced in recent years, with each purporting to offer a unique take on disrupting traditional financial instruments. Most fail to attract significant investment, but some grow quite valuable for at least a short time. This paper focuses on so-called "crypto unicorns", which reach a market capitalization of at least $1 billion at some point during their lifetimes. 37 coins and 139 tokens have reached unicorn status. However, only 15 coins and 35 tokens retain market capitalizations exceeding $1 billion at end of our study, with 6 coins and 31 tokens falling below $100 million. We empirically examine the factors that influence the relative success or failure of crypto unicorns. Using regression analysis, we find that bitcoin price, the type of service offered by the coin or token, having an ICO and social media activity all affect success.

Keywords: Cryptocurrency, Blockchain, Tokens, ICO, Empirical Analysis

1. Introduction and background

Over the past decade, the cryptocurrency market has experienced tremendous growth, reaching new highs repeatedly. However, this journey has been bumpy. A select few cryptocurrencies have performed exceptionally well in terms of market capitalization, while many others have struggled. The ecosystem remains plagued by bad actors who continually introduce Ponzi schemes and scam projects (Bartoletti et al., 2021; Li et al., 2023; Vasek and Moore, 2015). This persistent issue poses a significant obstacle to the successful adoption of a crypto-based financial system or any platform that relies on cryptocurrencies.

Cryptocurrencies can generally be categorized into two types: Coins and Tokens. Coins are cryptocurrencies that are mineable through proof-of-work or other consensus protocols, as established by their development teams and supported by factions of crypto enthusiasts. Tokens, on the other hand, are assets that developers can easily create on top of existing blockchain platforms such as Ethereum and Solana (termed *layer-2* in crypto-jargon). Since the introduction of Bitcoin, thousands of coins and tokens have been introduced and are traded on hundreds of cryptocurrency exchanges. One natural question is how have these assets performed financially over time. Another is what factors, if anything, drive the long-term success or failure of these coins.

Prior work has shed some light on these questions. Halaburda and Gandal, 2014 examined early competition among seven leading cryptocurrencies, finding no evidence of winner-take-all dynamics, in contrast to how other technology platforms behave. Instead, while Bitcoin has continued to lead in overall market share, its main impact has been to drive price fluctuations in other currencies both up and down (Halaburda, Haeringer, et al., 2022). Liu et al., 2022 investigated factors that affect cryptocurrency returns, finding that factors intrinsic to the cryptocurrency market are the best predictors. They also observed a strong time-series momentum effect for returns.

A number of researchers have investigated initial coin offerings (ICOs), in which tokens purporting to offer some functionality raise funds from investors in exchange for newly-minted coins. Howell et al., 2019 examined 1,500 ICOs and measured success through issuer employment and the associated company not failing. Adhami et al., 2018 identified factors associated with ICO success, notably publishing source code, organizing presales, and when tokens permit contributors to access services. A few studies have examined post-ICO trading performance of successfully launched tokens. Benedetti and Kostovetsky, 2018 study pricing in the month following launch, observing that tokens who reach the stage of trading on exchanges experience abnormally high returns of 48% within a month of listing. Fisch and Momtaz, 2020 take a slightly longer-term view of price performance six months after listing. They find that ICOs in which institutional investors have participated have greater success at the six-month mark.

Determining when a cryptocurrency is abandoned is not straightforward, as they may continue to be traded at low volumes similar to penny stocks. Exchanges often delist coins with low-trading volume, but the robust market in exchanges means that these coins can continue to be traded on less popular platforms. Alternative definitions of abandonment exist Fantazzini, 2022; Grobys and Sapkota, 2020.

In this paper, we also takes a broad view of cryptocurrency asset performance beyond just ICOs. However, we sidestep the challenge of defining abandonment by focusing on the winners. We limit our investigation "crypto unicorns," defined here as those exceeding a market capitalization of $1Bn[1]. We specifically exclude cryptocurrencies below this threshold. Only 176 coins and tokens, around 1% of exchange-traded cryptocurrencies, meet this definition. However, they hold the vast majority of wealth, with a combined market capitalization of $898Bn as of March 2023, 76% of the total across all coins and tokens tracked by Coinmarketcap.

The primary aim of our research is to investigate the factors contributing to the sustainability of success among these high-value cryptocurrencies. Through regression analysis, we demonstrate that the price of Bitcoin and Ethereum significantly affects the unicorns' own market capitalization, consistent with prior work. We find that the coin's purpose also affects unicorn market cap, with certain categories lagging. Finally, we find that social media activity is positively associated with success.

2. Methodology

2.1. Data sources

We gather data on coins and tokens from Coinmarketcap, the leading third-party cryptocurrency tracking service. We retrieved daily pricing, volume and market capitalization data for all listed coins and tokens for the decade April 2013–March 2023. In total we obtained data for more than 20,000 cryptocurrencies. Coinmarketcap also tags cryptocurrencies with common attributes, which we obtained for the coins under study. Coinmarketcap classifies cryptocurrencies as coins or tokens, which we follow.

We also gathered social media data from Coingecko. Cryptocurrencies have a massive social media following, especially on the subreddit pages where users interact and share their opinions and their experience building a community around cryptocurrencies. Coingecko reported the number of Reddit post, comments, and activity. We collected data posted on the first day of each month during a cryptocurrency's lifespan as proxy of community engagement and measured changes in activity every month.

Next, we aggregated the daily data into monthly data by computing the mean price, volume, and market cap of cryptocurrencies. We labeled coins as unicorns if they ever reached a mean market cap of $1 billion in any month. Finally, we manually referenced all identified unicorns against Icodrops to determine whether they raised funds through an ICO.

2.2. Research hypotheses

We seek to investigate the following questions with the gathered data.

- RQ1 The USD price of Bitcoin is positively correlated with unicorn market capitalization.
- RQ2 The USD price of Ethereum is positively correlated with unicorn market capitalization.
- RQ3 Bitcoin and Ethereum prices affect unicorn performance in later months.
- RQ4 Attributes of the coins and tokens (e.g., purported functionality, its use in smart contracts) affect performance.
- RQ5 Tokens that successfully raise funds through an ICO perform better.
- RQ6 Social media activity levels are positively correlated with performance.
- RQ7 Social media activity levels affect unicorn performance in later months.

RQ1–2 are consistent with the findings of prior work (Gandal et al., 2021; Halaburda, Haeringer, et al., 2022). RQ3 is motivated by the potential for unicorn

[1] According to Chen (2024, April), startups are defined as unicorns when they achieve a market capitalization of at least 1 billion dollars.

Table 1: Final market capitalizations (as of March 2023) of unicorn coins and tokens.

Market Capitalization	**Coin** #	**Coin** %	**Token** #	**Token** %	**Total** #	**Total** %
<$100M	6	16%	31	22%	37	22%
$100-550M	13	35%	51	37%	64	37%
$550M - 1B	3	8%	22	15%	25	14%
>$1B	15	41%	35	25%	50	28%
Total Count	37	100%	139	100%	176	100%

performance to lag the pricing swings of Bitcoin and Ethereum. RQ4 is motivated by the fact that there is such great diversity in strategies for coins and tokens, from their utility and how they interface with the broader ecosystem. RQ5 is consistent with prior work on ICOs, which found that most ICOs fail, but those that make it to the point of being actively traded on exchanges are more likely to continue operating in the long run. Finally, RQ7–8 are included because cryptocurrency trading is likely affected by social media promotions. In a sea of thousands of coins and tokens, those that have devoted followings are more likely to be successful and to attract more followers. The inverse is also likely to be true.

3. Descriptive statistics

We now describe relevant summary statistics for the observed crypto unicorns.

3.1. Market performance over time

176 cryptocurrencies achieve unicorn status by reaching an average monthly market capitalization of at least one billion dollars. However, not all stay above that threshold. In order to measure the relative success of unicorns, we create four categories outlined in Table 1.

Overall, 28% of unicorns remain so by the end of the study. By contrast, 22% of tokens have dropped in value by at least one full order of magnitude. The other half fall somewhere in the middle. Very little difference in final success is observed between tokens and coins.

Figure 1 plots the monthly market cap for two unicorns. The area under the curve is shaded to match each of the four performance categories. The top figure shows a relatively successful unicorn, Ethereum Classic, which first hit the $1 billion mark in early 2017. It fell below the threshold for a few years, then shot above the mark in late 2020 and remained above through the end of the data collection. By contrast, the bottom figure for Bancor shows a more volatile trend. It briefly became a unicorn in the last quarter of 2020. While it remained

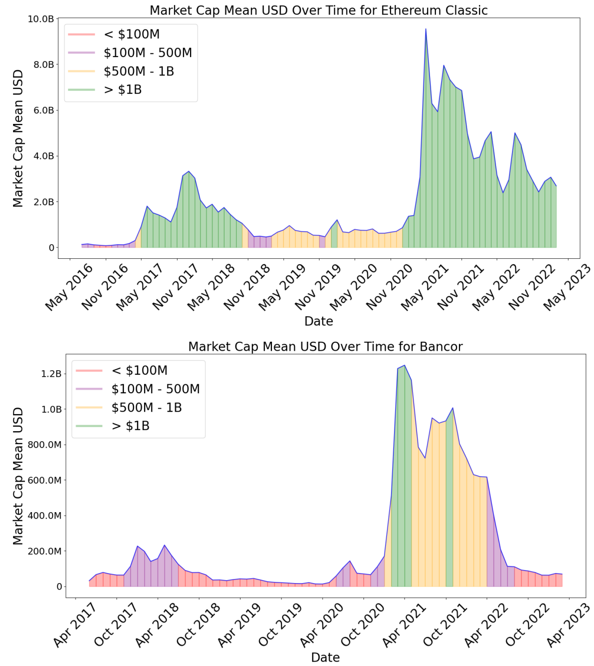

Figure 1: Market cap of persistent unicorn Ethereum Classic (top) and fleeting unicorn Bancor (bottom).

relatively successful for over a year, it then fell below 100 million dollars and stayed there.

Figure 2 shows unicorn performance over ten years. The top figure conveys the proportion, while the bottom plots the absolute number. It is evident from the plot that the number of unicorns have increased over the period of time. However, many thousands of cryptocurrencies were added during this time frame. Moreover, among the established unicorns, a sizeable proportion dropped in value to lower categories.

Figure 3 presents similar data slightly differently. The top figure shows the monthly count of once-unicorns whose market cap exceeds $1Bn and those below $100M. Right below is the BTC-USD and ETH-USD price. From visual inspection, it is clear that there is a strong relationship between these figures. The relationship is positive in the case of high market caps and negative for the low market caps.

3.2. Categories

In this section we describe the categorical variables associated with the cryptocurrencies we are examining. During the process of data collection we found lots of metadata associated with cryptocurrencies. Coinmarketcap permits user-defined tags. We identified 205 unique tags for the 176 cryptocurrencies we examined. We then computed the the top 10 most

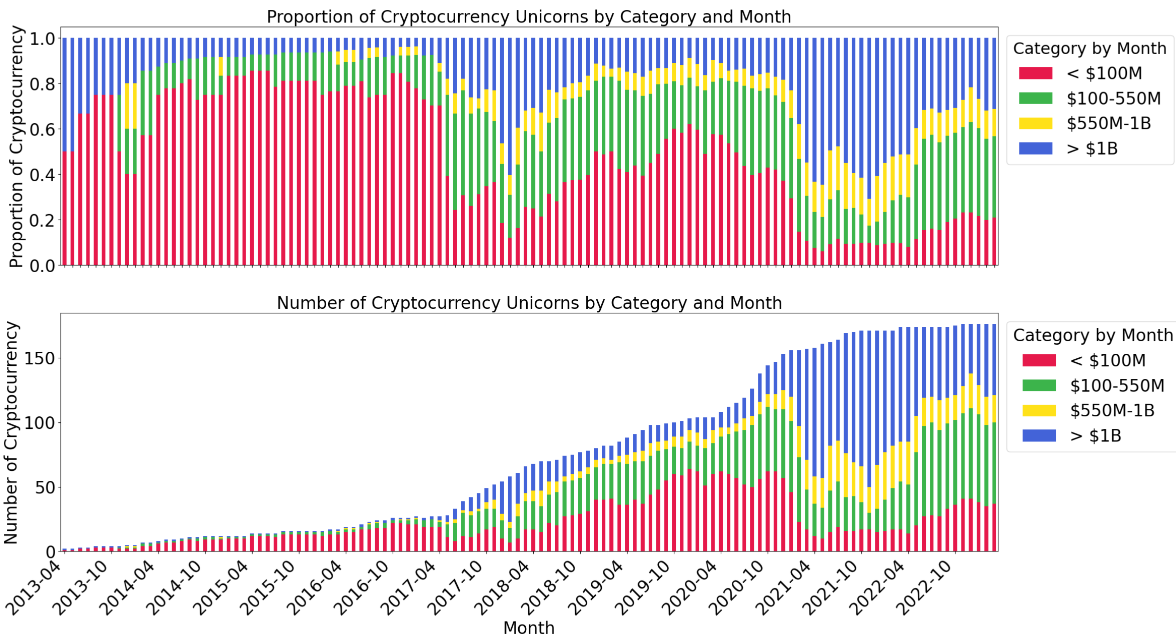

Figure 2: Proportion and number of unicorns over time in each category.

popular tags which are defined below.

According to coinmarketcap-glossary and bitget the categories are explained as follows:

- **DeFi** or Decentralized Finance refers to financial services and products built on blockchain technology, aiming to disrupt traditional financial systems by enabling peer-to-peer transactions without intermediaries.
- **Platform** refers to blockchain-based frameworks that provide a foundation for developing and deploying decentralized applications (dApps) and smart contracts.
- **Smart contracts** are self-executing contracts with the terms of the agreement directly written into code, enabling automatic, trustless transactions on the blockchain.
- **Layer-1** refers to the base layer or main blockchain architecture, such as Bitcoin or Ethereum, which directly processes and records transactions.
- **BNB Chain** (formerly Binance Smart Chain) is a blockchain platform developed by Binance, designed to support smart contracts and decentralized applications with high performance and low transaction costs.
- **Injective Ecosystem** refers to the network of decentralized finance applications and tools built on the Injective Protocol, a blockchain optimized for Decentralized finance derivatives and trading.
- **Mineable** refers to cryptocurrencies that are obtained through the process of mining, where computational power is used to solve complex algorithms and validate transactions on the blockchain.
- **Medium of exchange** refers to cryptocurrencies that are primarily used for transactions and payments, facilitating the exchange of goods and services.
- **Payments** refer to cryptocurrencies and blockchain solutions specifically designed to enable efficient, secure, and fast transactions and payment processing.
- **Alleged SEC securities** is related to coins and tokens that are allegedly considered as securities by SEC. They include some stable coins, exchange linked coins/tokens and some cryptocurrencies pegged with stocks and ETFs
- **ICO** or Initial Coin Offerings defines if external fund was raised for the development of a blockchain project similar to IPO (Initial Public Offering) for a startup. Blockchain companies provide coins/tokens to investors in exchange of

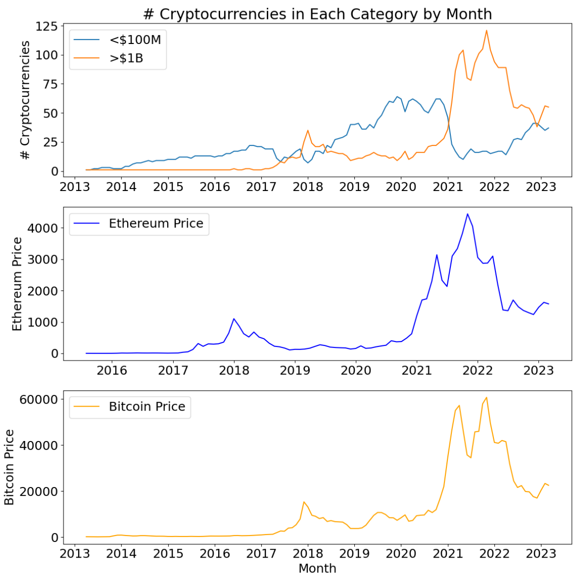

Figure 3: Unicorns over $1B and <$100M (top), ETH-USD (middle), and BTC-USD (bottom).

fiat currencies during nascent stage of the project which is used to develop and market the product.

Table 2 provides a detailed breakdown of the distribution of various categories of cryptocurrencies (both Coins and Tokens) across different market capitalization categories. Each row represents a specific category of cryptocurrency and includes the number of coins and tokens within that category, along with the percentage distribution of these cryptocurrencies within four market capitalization ranges: less than $100M, $100M to $550M, $550M to $1B, and greater than $1B.

One of the most striking observations is the dominance of Layer 1 projects in the high market cap segment, with a significant 65.51% of Layer 1 cryptocurrencies having a market capitalization greater than $1 billion. This suggests that Layer 1 projects tend to achieve higher valuations compared to other categories. Similarly, Alleged Securities also have a strong market presence, with 56.0% exceeding $1 billion in market capitalization, indicating high valuations despite potential regulatory scrutiny or the high valuation of the cryptocurrencies resulted in scrutiny from SEC especially as some of these cryptocurrencies are pegged with ETF and Stocks enlisted in US stock market.

In contrast, the DeFi and Platform categories show the highest concentration of cryptocurrencies in the $100 million to $550 million range, with 42.55% and 43.24%, respectively. This indicates a substantial number of mid-range valuations for these types of projects. The Injective Ecosystem displays a relatively even distribution across market cap categories, with a notable 42.30% exceeding $1 billion, suggesting a balanced presence across various market caps but also strong performance at the higher end.

ICO projects are concentrated in the middle and higher end of the market, with a significant 39% valued between $100 million and $550 million, and one third valued at over $1 billion.

4. Regression analysis

We now describe a series of regressions that seek to identify which factors are associated with sustained success of crypto unicorns. In particular, these regressions are used to test the research hypotheses outlined in Section 2.2.

Data for these regressions is in panel form aggregated at the monthly level. Time-dependent explanatory variables include the following: BTC-USD price, ETH-USD price, and Reddit Activity (all reported as monthly means). We also compute lagged variables for the preceding monthly values for each of these time-based variables. Fixed variables include the following: Is Coin (True if cryptocurrency type is Coin, False if token), # top tags, the top 10 tags each as Boolean variables if set (DeFi, Platform, Smart Contracts, Layer 1, BNB Chain, Medium of Exchange, Injective Ecosystem, Mineable, Payments), Had ICO (True if an ICO observed for the cryptocurrency). Summary statistics for these variables in panel form are given in Table 3.

4.1. Linear regressions

Selecting an appropriate response (i.e., dependent) variable can be challenging. When viewed primarily as a financial asset, long-term success for cryptocurrencies can best be captured by market capitalization. The most straightforward way to study market capitalization for unicorns is to directly track the market capitalization. We have run regressions with the market cap and its log transformation as the response variable. The results are materially unchanged from the regressions ultimately presented here.

One downside of directly using market capitalization is that it is highly volatile. The aim of our study is to investigate persistence of crypto unicorns; hence, we are most interested in whether these assets can maintain a billion-dollar level market capitalization once reached. For the linear regressions, the response variable is set to the price categories identified previously in Table 1. We converted the categories into numeric form [0-3]

Table 2: Cryptocurrency category prevalence split by market capitalization.

Tag Type	Type		<$100M		$100M - $550M		$550M - $1B		>$1B	
	# Coin	# Token	#	%	#	%	#	%	#	%
DeFi	4	43	9	19.14	20	42.55	6	12.76	12	25.53
Platform	12	25	5	13.51	16	43.24	3	8.10	13	35.13
Smart Contracts	11	25	4	11.11	15	41.66	4	11.11	13	36.11
Layer 1	9	20	0	0.0	5	17.24	5	17.24	19	65.51
BNB Chain	4	24	5	17.85	11	39.28	5	17.85	7	25.0
Injective Ecosystem	5	21	2	7.69	10	38.46	3	11.53	11	42.30
Mineable	25	0	4	16.0	11	44.0	3	12.0	7	28.0
Medium of Exchange	13	12	4	16.0	8	32.0	4	16.0	9	36.0
Payments	7	18	2	8.0	11	44.0	2	8.0	10	40.0
Alleged Securities	6	19	1	4.0	5	20.0	5	20.0	14	56.0
Funds Raised in ICO	12	57	8	11.59	27	39.13	12	17.39	23	33.33
Average %				11.9%		37%		13.2%		38%

Table 3: Summary statistics for regression variables.

Variable	Obs.	Mean	Std. Dev.
Log(BTC-USD Price)	9047	9.500	1.241
Log(ETH-USD Price)	8811	6.498	1.488
Reddit	3424	3222	22099
DeFi	9047	0.216	0.412
Platform	9047	0.235	0.423
Smart Contract	9047	0.236	0.424
Layer 1	9047	0.146	0.353
BNB Chain	9047	0.146	0.353
Mineable	9047	0.218	0.414
Medium of Exchange	9047	0.222	0.416
Payments	9047	0.174	0.378
Raised ICO	9047	0.402	0.490
Is Coin	9047	0.289	0.453
Category	9047	1.41	1.21
Unicorn	9047	.304	.460
<100M	9047	.308	.461

with 0 representing the **<$100M** (the least successful) group and 3 representing the highest classification of **>$1B** in market capitalization. Table 4 reports six linear regression models that investigate the research questions by incrementally adding explanatory variables.

We started by examining RQ1 and including only 2 variables. Coins are negatively correlated with higher performance, tokens positively correlated. The Bitcoin price is positively correlated. This is consistent with the visual correlations observed in Figure 3. It is worth noting that this simple model explains around 20% of the overall observed variance.

Regression 2 adds the Ethereum price, which is also positively correlated with higher performance. R^2 rises modestly, but the significance of BTC falls, suggesting that Ethereum's performance has a greater impact on unicorn performance than Bitcoin.

The third regression attempts to answer RQ4 and RQ5, namely, that the attributes of the cryptocurrency itself can influence its own long-run success. We added all the the category variables from Table 2 that list popular tags. Attributes such as DeFi and Platforms showed significant negative correlations, which means that these kinds of cryptocurrencies fared worse in terms of market capitalization. Because coins can have multiple tags, we also checked whether the number of top tags affected performance. It does seem to have a positive effect, though the significance is weaker. Note that in the linear regression, participating in an ICO does not seem to affect which performance category a cryptocurrency reaches. Collectively, these tags explain a lot of additional variance (R^2 rising to 0.32), which suggests that it is not only Bitcoin and Ethereum prices driving long-run performance.

One important question is whether BTC and ETH pricing only have an immediate effect, or if earlier performance could impact coins and tokens later on. In the fourth regression, we test RQ4 by adding one and two month lags for BTC and ETH prices. Lagged BTC and Lagged ETH Price. Lagged BTC price showed slightly significant positive correlation, but the ETH lags were more puzzling. We observed a high and strongly positive correlation one month before, but the correlation became strongly negative two months prior. Note that the additional variance explained is modest.

In the last two linear regression models we investigate RQ6 and RQ7. We see that social media

(Reddit) activity on a particular month is very highly positively associated with performance. However, social media activity in the immediately preceding month has no effect. Notably, while the number of observations falls substantially (since we do not have social media observations for all cryptocurrencies), the amount of explained variance rises substantially.

4.2. Logistic regressions

Since our primary interest is what makes crypto unicorns succeed or fail over the long term, we constructed two new binary response variables to capture relative success and failure. The first, Unicorn, is True for months when a cryptocurrency's market capitalization exceeds \$1 billion. The second, <\$100M, is True for months when the cryptocurrency's market capitalization falls below \$100 million. The former variable measures coin success, while the latter measures relative failure.

Table 5 shows a series of 7 logistic regressions where the dependent variables are Unicorn for the first 6 models and <\$100M for the complete model. Explanatory variables are incrementally added in the same sequence as for the linear regressions. The table shows the odds ratios and the t statistic in parentheses, rather than the coefficient, to improve interpretability. Any statistically significant odds ratio less than one indicates by how much the odds of the response variable being true are reduced, while any greater than one indicates an increase in odds.

When compared to the linear regressions, more variables are statistically significant (particularly with Unicorn as the response variable). The amount of variance explained is similar, as indicated by the log-likelihood values and the pseudo-R^2 values. Broadly speaking, results are consistent, supporting the research hypotheses similarly (though in a few cases, some explanatory variables are statistically significant only in the logistic regressions).

Equation 1 shows a 57% reduction in the odds of being a Unicorn for coins compared to tokens. Meanwhile, a one-unit increase in the natural logarithm of the bitcoin price corresponds to a 135% increase in the odds of a cryptocurrency being a Unicorn that month. In the next model, we added ETH price. Similarly, we saw significant increase in the odds of being classified as a unicorn by 92% if there is a 1 unit increase in natural log price of Ethereum on a particular month. Note that the Ethereum price remains positively correlated and significant across all 6 regressions, while the Bitcoin price is no longer significant.

When incorporating the tags in regression 3, we see a significant jump in the amount of variance explained. Each additional top tag added more than doubles the odds of being a unicorn. Many more tags are statistically significant. DeFi, platform, BNB chain, injective ecosystem, mineable and payments are negatively correlated, while Layer 1 and medium exchange are positively correlated. Meanwhile, cryptocurrencies with successful ICOs are associated with an 88% increase in the odds of being a unicorn.

Price lags do not make much impact, according to regression 4. Models 5 and 6 incorporate social media activity (Reddit). Higher Reddit activity on a particular month increases the likelihood of a coin becoming an unicorn but activity in previous months does not have any statistically significant effect. Notably, the explained variance for the model increases substantially once social media activity is incorporated.

Whereas the first 6 regressions studied success, in the last logistic regression, we changed the dependent variable to the lowest category, <\$100M. The idea here is to see what variables are associated with unicorns whose market share has fallen precipitously. In most cases, the signs flipped, as we might expect. The attributes that are positively associated with success are also negatively associated with failure.

For example, cryptocurrencies considered as a medium of exchange are associated with a 78% reduction in the odds of having such a low market capitalization. Raising funds via ICOs also decreases the odds by 73% of having a market cap lower than \$100 million. One difference is that social media activity, both in the current month and the one preceding, is negatively correlated with having a low market capitalization and is statistically significant.

4.3. Limitations

Our study is limited to the variables we could collect data for and use in the regression analysis. Undoubtedly, other factors could play a significant role. These could include shocks such such as regulatory changes or geopolitical events. Additionally, coin-specific activities such as on-chain transaction frequency and project software development could influence success. Further study is needed to explore these currently unobserved variables and measure how they might impact the sustainability of unicorn cryptocurrencies.

Additionally, while this study has identified significant correlations, more work is needed to establish causal relationships.

5. Conclusion

The supply of cryptocurrencies has exploded in recent years, due to low barriers to entry, a loosely regulated environment, and the prospects of fast riches. In this paper, we have investigated the long-run performance of the top 1% of coins and tokens that have reached a market capitalization of $1Bn at least once. These 176 coins and tokens account for the vast majority of cryptocurrency wealth, yet very little work has investigated what drives their long-run success or failure.

We have demonstrated that the price of Bitcoin and Ethereum plays a significant role, but that there are other factors at play, too. In particular, we showed that certain types of cryptocurrencies are more successful than others, and that tokens with successful ICOs tend to remain successful over the long term. Finally, we observe a correlation between social media activity in coin and token-specific forums and long-run performance.

References

Adhami, S., Giudici, G., & Martinazzi, S. (2018). Why do businesses go crypto? an empirical analysis of initial coin offerings [FinTech – Impact on Consumers, Banking and Regulatory Policy]. *Journal of Economics and Business*, *100*, 64–75. https://doi.org/https://doi.org/10.1016/j.jeconbus.2018.04.001

Bartoletti, M., Lande, S., Loddo, A., Pompianu, L., & Serusi, S. (2021). Cryptocurrency scams: Analysis and perspectives. *Ieee Access*, *9*, 148353–148373.

Benedetti, H. E., & Kostovetsky, L. (2018). Digital Tulips? Returns to Investors in Initial Coin Offerings. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3182169

Chen, J. (2024, April). Unicorn: What It Means in Investing, With Examples. Retrieved April 4, 2024, from https://www.investopedia.com/terms/u/unicorn.asp

Fantazzini, D. (2022). Crypto-coins and credit risk: Modelling and forecasting their probability of death. *Journal of Risk and Financial Management*, *15*(7). https://doi.org/10.3390/jrfm15070304

Fisch, C., & Momtaz, P. P. (2020). Institutional investors and post-ico performance: An empirical analysis of investor returns in initial coin offerings (icos). *Journal of Corporate Finance*, *64*, 101679. https://doi.org/https://doi.org/10.1016/j.jcorpfin.2020.101679

Gandal, N., Hamrick, J. T., Moore, T., & Vasek, M. (2021). The rise and fall of cryptocurrency coins and tokens. *Decisions in Economics and Finance*, *44*(2), 981–1014. https://doi.org/10.1007/s10203-021-00329-8

Grobys, K., & Sapkota, N. (2020). Predicting cryptocurrency defaults. *Applied Economics*, *52*(46), 5060–5076.

Halaburda, H., & Gandal, N. (2014). Competition in the Cryptocurrency Market. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2506463

Halaburda, H., Haeringer, G., Gans, J., & Gandal, N. (2022). The microeconomics of cryptocurrencies. *Journal of Economic Literature*, *60*(3), 971–1013.

Howell, S. T., Niessner, M., & Yermack, D. (2019). Initial Coin Offerings: Financing Growth with Cryptocurrency Token Sales. *The Review of Financial Studies*, *33*(9), 3925–3974. https://doi.org/10.1093/rfs/hhz131

Li, X., Yepuri, A., & Nikiforakis, N. (2023). Double and nothing: Understanding and detecting cryptocurrency giveaway scams. *Proceedings of the Network and Distributed System Security Symposium (NDSS)*.

Liu, Y., Tsyvinski, A., & Wu, X. (2022). Common Risk Factors in Cryptocurrency. *The Journal of Finance*, *77*(2), 1133–1177. https://doi.org/10.1111/jofi.13119

Vasek, M., & Moore, T. (2015). There's No Free Lunch, Even Using Bitcoin: Tracking the Popularity and Profits of Virtual Currency Scams [Series Title: Lecture Notes in Computer Science]. In R. Böhme & T. Okamoto (Eds.), *Financial Cryptography and Data Security* (pp. 44–61, Vol. 8975). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-662-47854-7_4

Table 4: Linear regression models.

	(1) category	(2) category	(3) category	(4) category	(5) category	(6) category
Is Coin	-0.451**	-0.450**	-0.222	-0.212	-0.151	-0.138
	(0.141)	(0.142)	(0.227)	(0.231)	(0.303)	(0.309)
log (BTC-USD Price)	0.522***	0.0545*	0.0540*	0.0148	0.0124	0.0237
	(0.00761)	(0.0249)	(0.0249)	(0.0249)	(0.0443)	(0.0528)
log (ETH-USD Price)		0.372***	0.373***	0.271***	0.316***	0.356***
		(0.0177)	(0.0177)	(0.0189)	(0.0354)	(0.0451)
# Top Tags			0.383*	0.402*	0.691*	0.669*
			(0.167)	(0.169)	(0.288)	(0.297)
DeFi			-0.409*	-0.482*	-0.653	-0.620
			(0.202)	(0.205)	(0.348)	(0.359)
Platform			-0.653**	-0.670**	-0.904*	-0.788
			(0.244)	(0.247)	(0.404)	(0.413)
Smart Contracts			-0.105	-0.0976	-0.0748	-0.0627
			(0.209)	(0.212)	(0.309)	(0.318)
Layer 1			0.183	0.185	-0.168	-0.184
			(0.253)	(0.256)	(0.459)	(0.478)
BNB Chain			-0.254	-0.334	-0.822*	-0.783*
			(0.218)	(0.221)	(0.365)	(0.374)
Medium of Exchange			0.161	0.0983	0.137	0.169
			(0.239)	(0.242)	(0.395)	(0.403)
Injective Ecosystem			-0.270	-0.238	-0.909*	-0.862*
			(0.237)	(0.241)	(0.368)	(0.379)
Mineable			-0.308	-0.369	-0.563	-0.579
			(0.310)	(0.314)	(0.489)	(0.504)
Payments			-0.429	-0.400	-1.075**	-1.058**
			(0.256)	(0.260)	(0.396)	(0.406)
Had ICO			0.206	0.213	0.312	0.343
			(0.117)	(0.118)	(0.204)	(0.211)
1 mo. Lagged BTC Price				0.568*	1.947	-1.455
				(0.273)	(2.167)	(5.370)
2 Mo. Lagged BTC Price				0.336	-0.914	2.557
				(0.237)	(2.096)	(5.358)
1 Mo. Lagged ETH Price				0.000260***	0.000250***	0.000178**
				(0.0000225)	(0.0000506)	(0.0000587)
2 Mo. Lagged ETH Price				-0.0000697***	-0.000121**	-0.0000856
				(0.0000208)	(0.0000467)	(0.0000533)
Reddit					0.0345***	0.0373***
					(0.00735)	(0.0107)
1 Mo. Lagged Reddit						0.00505
						(0.0102)
Constant	-2.822***	-0.766**	0.364	1.363	3.387	2.716
	(0.267)	(0.293)	(1.681)	(1.704)	(2.830)	(2.933)
N	9047.000	8811.000	8811.000	8452.000	1834.000	1359.000
R-Squared	0.197	0.215	0.320	0.357	0.481	0.490

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Logistic regression models.

	(1) Unicorn	(2) Unicorn	(3) Unicorn	(4) Unicorn	(5) Unicorn	(6) Unicorn	(7) <$100M
Is Coin	0.431***	0.433***	0.637***	0.644***	0.669	0.638	1.083
	(-15.17)	(-14.73)	(-3.99)	(-3.74)	(-1.39)	(-1.30)	(0.22)
log(BTC-USD Price)	2.351***	1.118	1.129	1.043	0.829	0.809	1.481
	(29.18)	(1.34)	(1.34)	(0.44)	(-0.97)	(-0.95)	(1.79)
log(ETH-USD Price)		1.919***	2.235***	1.869***	3.317***	3.751***	0.224***
		(10.46)	(11.84)	(7.61)	(6.58)	(6.01)	(-7.38)
# Top Tags			2.529***	2.809***	3.175***	3.971***	0.691
			(11.55)	(12.45)	(4.54)	(4.48)	(-1.04)
DeFi			0.299***	0.237***	0.0937***	0.0606***	0.672
			(-11.98)	(-13.60)	(-7.31)	(-7.09)	(-0.92)
Platform			0.170***	0.163***	0.103***	0.105***	2.171
			(-14.58)	(-14.50)	(-6.03)	(-4.98)	(1.70)
Smart Contracts			0.873	0.892	1.623	1.309	0.413*
			(-1.36)	(-1.11)	(1.64)	(0.74)	(-2.16)
Layer 1			1.597***	1.538***	2.739*	2.117	0.236*
			(3.85)	(3.44)	(2.26)	(1.38)	(-2.23)
BNB Chain			0.456***	0.349***	0.0576***	0.0490***	0.649
			(-7.17)	(-9.16)	(-7.33)	(-6.52)	(-0.95)
Medium of Exchange			1.271*	1.203	2.173*	2.021	0.217***
			(2.24)	(1.68)	(2.51)	(1.89)	(-3.48)
Injective Ecosystem			0.663***	0.695**	0.457*	0.440*	2.371
			(-3.50)	(-2.99)	(-2.34)	(-1.99)	(1.93)
Mineable			0.498***	0.413***	0.492	0.300	0.863
			(-4.67)	(-5.71)	(-1.36)	(-1.86)	(-0.22)
Payments			0.287***	0.291***	0.0784***	0.0603***	1.726
			(-10.17)	(-9.77)	(-6.82)	(-6.22)	(1.16)
Had ICO			1.887***	1.907***	2.786***	2.732***	0.263***
			(10.73)	(10.49)	(5.16)	(4.46)	(-5.70)
1 Mo. Lagged BTC Price				4.484	236529.3	6432169.9	3.06e-24
				(1.83)	(0.51)	(0.62)	(-1.24)
2 Mo. Lagged BTC Price				2.803	0.000218	0.00000673	2.74973e+22
				(1.27)	(-0.35)	(-0.47)	(1.18)
1 Mo. Lagged ETH Price				1.000***	1.001*	1.000	1.000
				(6.13)	(2.57)	(1.23)	(0.32)
2 Mo. Lagged ETH Price				1.000**	1.000**	1.000	1.000
				(-3.17)	(-2.66)	(-1.44)	(0.68)
Reddit					1.108***	1.105*	0.886**
					(3.90)	(2.30)	(-2.66)
1 Mo. Lagged Reddit						1.020	0.907*
						(0.47)	(-2.24)
N	9047.000	8811.000	8811.000	8452.000	1834.000	1359.000	1359.000
Log-Likelihood	-4929.229	-4760.898	-4154.641	-3889.423	-665.001	-505.178	-480.572
Pseudo R^2	.1132	.1263	.2375	.2661	.4149	.4131	.4177

Exponentiated coefficients; *t* statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$