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Striking Gold in Software Repositories? An Econometric Study of Cryptocurrencies on GitHub

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***Abstract*—Cryptocurrencies have a significant open source development presence on GitHub. This presents a unique opportunity to observe their related developer effort and software growth. Individual cryptocurrency prices are partly driven by attractiveness, and we hypothesize that high-quality, actively-developed software is one of its influences. Thus, we report on a study of a panel data set containing nearly a year of daily observations of development activity, popularity, and market capitalization for over two hundred open source cryptocurrencies. We find that open source project popularity is associated with higher market capitalization, though development activity and quality assurance practices are insignificant variables in our models. Using Granger causality tests, we find no compelling evidence for a dynamic relation between market capitalization and metrics such as daily stars, forks, watchers, commits, contributors, and lines of code changed.**

***Index Terms*—cryptocurrency, open source software, github, software metrics, software quality**

I. Introduction

What drives the price of cryptocurrencies? Due to their decentralization, they may be strongly driven by social factors [1] and the whims of speculators [2]. Previous studies suggest that popularity is dynamically related to the value of cryptocurrencies, *e.g.*, according to econometric analysis of short-term data from Google Trends and Wikipedia [2], [3], as well as to sentiment expressed on Twitter [4] and other socio-economic signals [1].

Cryptocurrencies have a high standing in the open source development community, with some of the most popular repositories on GitHub including coins such as Bitcoin, Ripple, and Ethereum. Previous research indicates that developers use signals of popularity and activity on GitHub to assess project quality [5], and that quality assurance practices are associated with positive outcomes [6]–[8]. In light of this, we hypothesize that high-quality, actively-developed software is one component of the attractiveness of cryptocurrencies.

Although metrics such as lines of code and commit history do not necessarily speak to software quality (indeed, evaluating software quality is a longstanding problem in research [9]–[12]), prior work shows that quantitative metrics can be useful as covariates for software quality predictors [13] and maintenance [14]. To the extent that such metrics are proxies for software quality, they should also be associated with value, *e.g.*, operationalized by the market capitalization (market cap) of the associated cryptocurrency. Cryptocurrencies thus also present a unique opportunity to explore the potential of quickly profiting financially from repository mining techniques.

In this paper we pose the following research questions:

- RQ_1: Do metrics of activity, popularity, and quality assurance explain variance in cryptocurrency market caps?
- RQ_2: Is there a dynamic relation between these software metrics and market cap?

We follow an econometric approach to answer these questions, using dynamic regression models for panel data with autoregressive errors and doing Granger causality analysis. While our models suggest that popular projects have a significantly higher average market cap, other variables held equal, we find no compelling evidence of a dynamic relation between software-related metrics and daily market cap.

II. Experiment Setup and Data Set

Starting on January 21, 2018, we began collecting a longitudinal (*i.e.*, panel) data set of 241 cryptocurrency projects on GitHub. At the time of writing, this data is still being recorded each day; currently, each project has 347 daily observations. On January 21, 2018, we ranked the top 339 cryptocurrencies by market cap on CoinMarketCap and manually confirmed those with GitHub repository links. The remainder did not develop open source artifacts or were hosted elsewhere.

From the GitHub API, we recorded the number of daily commits, contributors, lines of code added and removed, stars, forks, and watchers (*i.e.*, subscribers) for thousands of repositories that comprise the cryptocurrency projects and organizations. Additionally, we collected financial data for each cryptocurrency: the price and *market capitalization* (*i.e.*, price $\times$ coins available) from CoinMarketCap, [15] one of the leading sites in indexing cryptocurrencies.

These metrics broadly capture the size and growth of projects in terms of popularity and developer activity. The historic number of repository stars, forks, and watchers are short-lived, so our data set is unique in storing the daily values of these metrics for thousands of repositories. In particular, repository watcher information is not exposed in GitHub's event stream, so it cannot be collected from GHTorrent [16]. The data set also contains the number of commits and lines of code added and removed in the last 24 hours, as well as the number of unique active developers in the last 7 days for each day.

For each repository, we also record whether it is *forked*: for example, the Bitcoin organization has four repositories: `bitcoin`, `bips`, `libblkmaker`, and `libbase58`. The `libbase58` project was forked from another developer; hence, we must decide whether it reflects the development activity

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and popularity of BITCOIN. Cryptocurrency projects may have as few as one repository, *e.g.*, XTRABYTES, or as many as 567, *e.g.*, LYKKE. Thus, our complete data set contains longitudinal metrics for 6,654 repositories, though we consider each cryptocurrency as an aggregate of its repositories.

Through manual inspection, we removed 71 projects that did not have enough development activity or financial data in the past year to be investigated. Some of these projects moved repositories, rebranded, or became defunct (*e.g.*, [17]). Our data collection tool is extensible and open source.[1] More details on the tool and data set can be found in a related data showcase submission [18].

We also collected repository badges using the same method as Trockman et al. [6], and recorded the presence of Continuous Integration (CI) by detecting the configuration files of the popular CI services TRAVIS CI, CIRCLECI, and APPVEYOR.

To answer RQ_1, we model the averages of our collected data over the past year; for RQ_2, we model the daily changes.

III. ANALYSIS

Our analysis proceeds in five complementary steps. (1) First, we investigate pairwise linear (Pearson) correlations between average market cap and software metrics in the last year. While many of these metrics positively correlate with market cap, they may be confounded with or insignificant in comparison to other metrics; hence, (2) we fit linear models of average market cap to assess metrics with others held fixed. We then ask if changes to these metrics over time are associated with corresponding changes in market cap: (3) We fit dynamic linear regression models of daily market cap versus fluctuations in various metrics, and (4) we investigate Granger causality between market cap and other time series metrics. (5) Finally, suspecting that the relationship may be non-linear, we train simple multilayer perceptrons to predict future market cap. We test all hypotheses at the $\alpha = 0.05$ level, controlling for multiple comparisons [19], [20].

A. Yearly Averages

Bivariate investigation. We aggregate our data set by computing the yearly average of each metric for all 347 days observed: stars, forks, watchers, commits, LOC added, LOC removed, unique contributors, and market cap. We remove forked repositories from the aggregates in this step of the analysis. Trockman et al. [6] found that the presence of badges is a "mostly reliable" signal of best practices and software quality based on a survey of developers and quantitative analysis. Hence, we also investigate the association between badges, a binary variable, and market cap; we say that a cryptocurrency uses badges if its most starred repository has one or more badges of any type. Further, CI is widely considered to be associated with well-tested, high-quality software, so we introduce a binary variable if the most starred repository has traces of one or more third-party CI services.

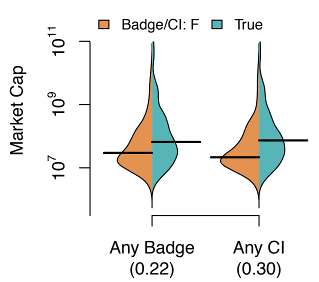


Fig. 2: Slightly higher avg. market cap for coins using badges or CI. (N=126+78=97+107)

[1]https://github.com/rvantonder/CryptOSS

We found significant correlations between our studied measures and market capitalization: stars 62%, watchers 61%, forks 65%, unique contributors 50%, commits 43%, LOC added 38%, and LOC removed 32%. Moreover, cryptocurrencies using badges have a significantly higher $\log_{10}$ average market cap than those without, with respective medians of 7.7 and 7.3. Similarly, for cryptocurrencies using CI, we have medians of 7.7 and 7.2 (see Fig. 2). Hence, we find evidence in support of RQ_1: badges, CI, and popularity metrics are associated with higher market cap, and to a lesser extent, so are development activity metrics. However, these metrics are inter-related, *e.g.*, more popular projects are more likely to have badges.

Linear models. Hence, we fit linear models of the average market cap in the last year. First, after inspecting histograms, we did a logarithmic transformation of all continuous variables. We inspected residual plots for uniformity and removed high-leverage points having a Cook's distance greater than $\frac{4}{n}$.

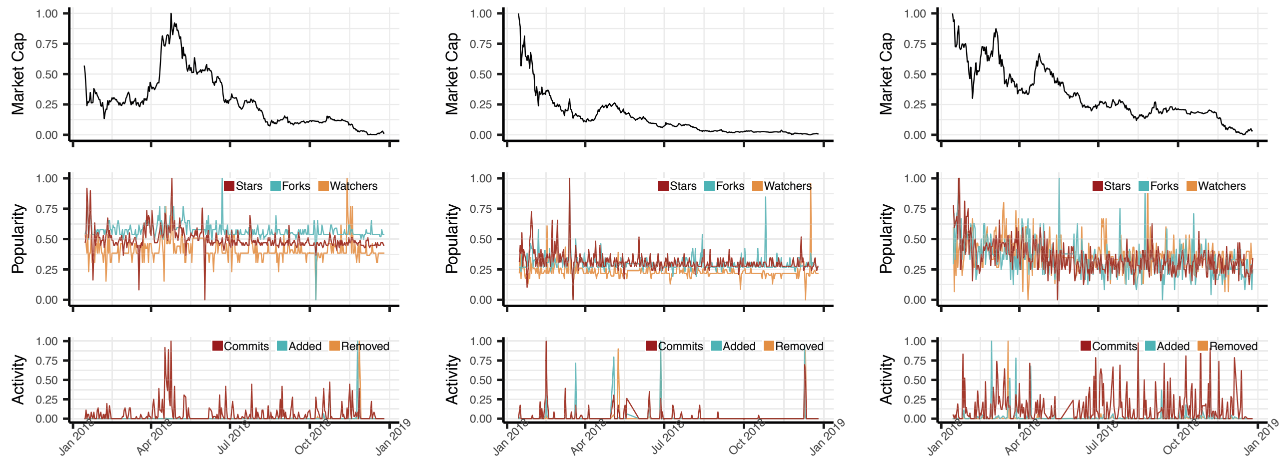
The groups of popularity and activity metrics are collinear, resulting in high variance inflation factors (VIFs). Hence, we fit two types of models: a basic model, where we remove variables until all VIFs are < 3 [21], and a full model, where VIFs are greater. In the full models, we cannot assess the significance of individual coefficients due to inflated standard errors; however, the coefficients remain unbiased. We expect, for example, that forks and watchers contain valuable information despite their near-collinearity with stars. Instead, we test *joint hypotheses* [22] using the F-test, *e.g.*, H_0 : stars $=$ forks $=$ watchers $= 0$. In our basic models, we find that only stars are significant: a 1% increase in the star count is associated with a 0.7% increase in market cap. In the full models, we find that only the three popularity metrics are jointly significant. The basic model explains 42.7% of the variance, while the full model explains 53.7% (see Table Ia).

We thus find that our popularity metrics are significantly and positively associated with average market cap, while *activity and quality assurance metrics provide no significant information gain over them.* The results hold similarly whether or not forked repositories are considered.

B. The Last Year's Trend

We now investigate if there is a dynamic relation between cryptocurrency market cap and the studied metrics.

Dynamic regression. In the analysis of financial time series, it is conventional to model log returns, *i.e.*, the first difference of the log of the series, due to its desirable statistical properties [23]. We instead choose to model the first difference of the log of market cap, which we found to be stationary by applying the Augmented Dickey-Fuller (ADF) test [24] to each individual series. For this dependent variable, we construct linear mixed-effects models with autoregressive covariance structures; we



(a) **Bytom.** Commits Granger-cause market cap: note the spike in both commits and market cap around April 2018.

(b) **NEM.** Stars Granger-cause market cap: stars per day are comparatively high while the market cap is plunging around Jan. 2018.

(c) **Monero.** None of the studied metrics Granger-cause market cap.

Fig. 1: Representative examples of cryptocurrency time series of market cap, popularity, and development activity.

investigate whether daily changes in stars, forks, watchers, commits, LOC added/removed, and unique contributors are associated with changes in market cap log "returns".

We removed projects with more than 320 days without additional stars or commits, leaving 125 projects for our analysis. Then, we determined that the series of stars, forks, watchers, and contributors are non-stationary using the ADF test, and thus took the first differences of their logs; commits and LOC changes are already stationary. Our models include a random intercept for each cryptocurrency to account for intra-coin differences in market cap. By iteratively fitting models and inspecting residual autocorrelation plots, we selected an ARMA$(1,1)$ covariance structure; and included the previous day's market cap log "returns" as control.

The popularity metrics were jointly significant in the model without forks, but insignificant in the model with forks; we have limited evidence that there is a dynamic relationship between popularity and market cap. Both models explain around 15% of the variance in market cap, with the previous market cap being the most important variable (see Table Ib).

Granger causality investigation. We now ask if any of the studied metrics can help to explain future market caps: A series X is said to *Granger-cause* Y if past values of X are useful in forecasting Y, controlling for past values of Y [22], [25]; *e.g.*, if γ is statistically significant in

$$y_t = \delta_0 + \sum_{j=1}^{p} \alpha_j y_{t-j} + \sum_{j=1}^{p} \gamma_j x_{t-j} + \epsilon_t.$$

We test whether popularity and activity metrics (x_t) Granger-cause market cap (y_t), a standard technique in econometrics. To avoid spurious results we follow the Toda-Yamamoto procedure, which is robust to the integration and cointegration properties of the series and avoids pre-test bias due to the low statistical power of the ADF test [26]; *i.e.*, we do not have to test and difference the series before fitting the models.

First, we fit a vector autoregressive (VAR) model [27] with two endogenous variables, market cap and one of our metrics, as we expect that market cap and popularity or activity could each cause the other. We choose the number of lags using the Akaike Information Criterion (AIC) [28]. To ensure that the Wald test statistic of the γs follows its expected asymptotic distribution, we add d additional lags to the model, where d is the maximum order of integration of the two series, determined by the ADF and KPSS [29] tests [26]. We then test if the model is misspecified using the Portmanteau test for serially correlated errors [27]. If this process fails, we attempt to add up to ten lags before eliminating the cryptocurrency due to the possibility of spurious regression from misspecification [30].

We checked all market cap series for structural breaks, which can also result in spurious regression. Using the Chow test [31], [32], we determined that almost all projects have a break near February 25, 2018, so we excluded all days up to this point from our analysis. We correct for multiple hypothesis testing using the false discovery rate (FDR) of Benjamini and Hochberg [19], [20]. Finally, we scale all series to the same range and then test for Granger non-causality between a given metric and market cap using the Wald χ^2 test.

We found evidence of Granger causality from stars to market cap for just 9 of 142 projects fulfilling the above criteria, 4/146 watchers to market cap, and 3/147 forks to market cap. Only one project occurs in two of the cases: NEM for both watchers and forks. For activity metrics, we found only 2/130 cases of Granger causality from commits to market cap, 2/136 for LOC added, and none for LOC removed and contributors. In the opposite direction, *i.e.*, market cap causing increased popularity or activity, we found similar results: notably, 7/146 cases for watchers. See Fig. 1 for examples.

TABLE I: Linear regression models of market cap and log market cap returns. Note that individual independent variables cannot be interpreted due to high multicollinearity; see joint hypothesis tests instead.

(a) Models of average metrics in the last year

	Dependent variable: $\mu \log$ *Market Cap (1y)*			
	Basic Model No forks	**Full Model** No forks	**Basic Model** With forks	**Full Model** With forks
μ logStars	$0.70\ (0.36)^{***}$	0.15 (0.16) Joint ***	$0.73\ (0.36)^{***}$	0.29 (0.18) Joint ***
μ logWatchers		0.02 (0.20)		0.03 (0.20)
μ logForks		0.54 (0.16)		0.47 (0.17)
μ logCommits	0.05 (0.15)	0.24 (0.30)	0.06 (0.14)	0.35 (0.30)
μ log+LOC		0.14 (0.07)		0.08 (0.08)
μ log−LOC		−0.13 (0.07)		0.08 (0.08)
μ logContrib.		0.01 (0.32)		0.31 (0.31)
HasBadge	−0.31 (0.27)	−0.34 (0.25)	−0.07 (0.22)	0.21 (0.21)
HasCI		−0.06 (0.23)		0.23 (0.23)
(Intercept)	$14.5\ (0.36)^{***}$	$14.4\ (0.47)^{***}$	$14.1\ (0.36)^{***}$	$14.0\ (0.48)^{***}$
Observations	167	149	169	149
Adj. R^2	42.7%	53.7%	46.6%	55.6%

(b) Dynamic regression models

	Dependent variable: $\nabla \log \text{M. Cap}_t = \log \left(\text{M. Cap}_t / \text{M. Cap}_{t-1}\right)$			
	Basic Model No forks	**Full Model** No forks	**Basic Model** With forks	**Full Model** With forks
$\nabla \log \text{M. Cap}_{t-1}$	$5.46\ (0.05)^{***}$	$5.30\ (0.05)^{***}$	$5.38\ (0.04)^{***}$	0.51 (0.00)
$\nabla \log \text{Stars}_t$	−0.04 (0.04)	−0.02 (0.04) Joint **	0.00 (0.04)	−0.01 (0.05)
$\nabla \log \text{Forks}_t$		−0.59 (0.17)		−0.22 (0.20)
$\nabla \log \text{Watchers}_t$		0.46 (0.18)		0.32 (0.18)
$\log \text{Commits}_t$	0.00 (0.00)	0.01 (0.01)	0.00 (0.00)	0.00 (0.01)
$\log \text{+LOC}_t$		0.00 (0.00)		0.00 (0.00)
$\log \text{-LOC}_t$		−0.00 (0.00)		−0.00 (0.00)
$\nabla \log \text{Contrib.}_t$		−0.03 (0.02)		−0.01 (0.02)
(Intercept)	$-0.04\ (0.00)^{***}$	$0.04\ (0.00)^{***}$	$0.04\ (0.00)^{***}$	$-0.00\ (0.00)^{***}$
Observ. (N×T)	112×345	112×345	125×345	125×345
R_c^2	15.9%	15.3%	15.6%	15.3%
ARMA(p,q)	$(1,1)$	$(1,1)$	$(1,1)$	$(1,1)$

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}\mathbf{p < 0.05}$

Importantly, Granger causality does not imply a *positive* relationship, and despite precautions, our method is sensitive to sudden changes in level or volatility: upon manual inspection, many cases appeared to be single contemporaneous spikes in metrics and market cap. Hence, we conclude that we have no compelling evidence for Granger causality between popularity metrics, development activity metrics, and market cap. If we first remove sparse series (which do not fit model assumptions closely) as in Sec. III-B, our results are yet weaker, *e.g.*, only one project exhibits Granger causality from stars to market cap.

IV. Discussion and Conclusion

Research questions. Using long-term averages as well as short-term daily fluctuations in market cap versus software-related metrics, we found limited evidence that repository data are associated with the price of cryptocurrencies. Unsurprisingly, we found that popularity operationalized, *e.g.*, as stars, is associated with a higher average market cap, even with other factors held equal. Hence, we find some evidence in support of RQ_1: metrics of popularity explain variance in average market capitalizations in the last year. While we found that quality assurance (operationalized as the presence of badges or CI) is correlated with average market cap, it is insignificant in our multiple regression models. The results are similarly insignificant for commits, contributors, and LOC changes.

For RQ_2, we investigated the dynamic relationship between market cap and our studied metrics with time series analysis techniques. We found some evidence that popularity is dynamically related to market cap, though the result changed when including forked repositories. We investigated bidirectional Granger causality between market cap, popularity, and activity. We found few projects showing significant effects; hence, we conclude that we found no compelling evidence for RQ_2.

Threats to validity. We used linear modeling techniques that rely on assumptions which are often violated by financial time series; the true relationship could be non-linear, or it could have a long memory. To investigate non-linearity, we fit small multi-layer perceptrons for a one-day forecast given up to three days of past information and evaluated them on a held-out test set. In our limited testing, predictions were entirely random and unimproved by the addition of software metrics.

We noticed violations of the assumptions of the models used, *e.g.*, non-Gaussian series, structural breaks, and extreme outliers, though these often make it *easier* to reject the null hypothesis, *e.g.*, in the case of structural breaks [33].

For some 19 days, observations were missed due to our server outage. Where possible, we recovered data from GitHub, GHTorrent, and CoinMarketCap. For forks and subscribers we used linear interpolation. Missing and recovered data had a negligible impact on our results.

The relationship between software quality and market cap may be longer-term than studied. We noticed that many cryptocurrencies experienced an overall downward trend in the past year, which could explain our negative results.

Related Work and Conclusion. Applications and challenges of cryptocurrencies are a topic of active research [34], and econometric properties have been studied for socio-economic signals [1]–[4], [35]. Our study investigates cryptocurrency values (market capitalization) in the last year for over 200 open-source cryptocurrencies on GitHub using repository data. We were primarily interested in whether developer activity and interaction (repository badges, contributors, commits, stars, etc.) could explain price variance of cryptocurrencies. We found that popularity metrics (*i.e.*, stars) are significantly positively associated with average market cap on average over the past year, while activity and quality assurance metrics provide no significant information gain over them. We found limited evidence for a dynamic relationship between popularity and market cap, with no compelling evidence to support forecasting via Granger causality tests.

The outlook for cryptocurrencies remains unpredictable, but our results show that mining their software artifacts presents an interesting direction for research and analysis: future work may investigate longer-term, multi-year trends in the price, volatility, volume, or number of users. We look forward to the continued development of cryptocurrencies and whether their success will be mirrored by software quality and effective software engineering over time.

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