HEDONIC PRICING OF CRYPTOCURRENCIES

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Abstract

A big data set consisting both GitHub and market metrics have been utilized to decompose the inherent attributes of 240 cryptocurrencies' effects on the price. Three main aspects of projects were considered: Popularity, Maintenance and Competition. Majority of the related variables are distributed as Gaussian, and, only the tail distribution of cryptocurrency supply follows a power law. It turns out that supply side popularity of cryptocurrencies are the most important driving force among others. Crypto-asset prices are being dominated by the supply side participants' actions. Moreover, long- term maintenance of cryptocurrency projects have no effect on their prices. It can be said that valuation-span of market participants is extremely short-sighted.

Keywords: Cryptocurrencies, Hedonic Pricing, Order Statistics, Hill Estimator, Kolmogorov-Smirnov Test, Three-dimensional Linear Estimation

JEL Classification: C55, C58, D1, D3, D46, G1, G23, L86

Öz

240 kripto paranın içsel özelliklerinin fiyat üzerindeki etkilerini ayrıştırmak için GitHub ve piyasa verilerinden oluşan bir büyük veri seti kullanılmıştır. Projeler üç ana yönden göz önüne alınmıştır: Popülerlik, Bakım ve Rekabet. İlgili değişkenlerin çoğunluğu Gaussian dağılıma sahip olmakla birlikte, yalnızca kripto para arzının kuyruktaki dağılımı güç yasasına uymaktadır. Kripto paraların arz yönlü popülerliği diğerlerine göre en önemli belirleyici olarak öne çıkmaktadır. Kripto varlık fiyatları arz tarafındaki katılımcıların aksiyonları tarafından domine edilmektedir. Ayrıca kripto para projelerinin uzun vadeli bakım/onarımları fiyatları üzerinde hiçbir etkiye sahip değildir. Piyasa katılımcılarının değerleme ufkunun oldukça miyop olduğu söylenebilir.

Anahtar Kelimeler: Kripto para, hedonik fiyatlama, sıra istatistikleri, Hill tahmincisi, Kolmogorov-Smirnov Testi, Üç boyutlu doğrusal tahmin

JEL Sınıflaması: C55, C58, D1, D3, D46, G1, G23, L86

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1. Introduction

The second decade of the twentieth century witnessed the dawn of cryptocurrencies. Although most people had foreseen the information to become an important source of the prospect in the new age, not many would expect it to be as literal. The cryptocurrencies can be oddly defined as strings of (mainly useless) secured information. They can be obtained by contributing to its functioning or bought from a holder in exchange of money, and they are generally transferable.

According to a recent survey, while 52% of the cryptocurrency holders see it as a source of income instead of a hobby, 15% of cryptocurrency users consider it as their primary income source (Binance Research, 2021). There are hundreds, if not thousands, cryptocurrencies and several types such as coin or token, but Bitcoin has been a generic subject to start the investigation in the literature. When it comes to label Bitcoin as gold or currency, researchers (like social media promoters) stand righteously firm. However, it does not get treated academically with similar elegance like monetary economics. Analyzing the price of a fiat money, e.g. central banking, is a colossal undertaking. Papers on Bitcoin price relentlessly try to predict its price on empirically simple and unrelated frameworks. The main shortcoming of such undertakings is the lack of appropriate economic theory related to supply and demand of Bitcoin. There are many successful efforts to make it seem like a solid line of work (e.g. Awoke et al. (2021)) but the main argument suffers from hypothetical assumptions that it is readily accepted as a currency. This labeling process is not within the scope of this paper, though. An early work by Böhme et al. (2015) presented the initial framework of Bitcoin and how to treat it academically. It paved the way for research on cryptocurrencies, while none of the mentioned, and widely popular aside the paper, possibilities for Bitcoin's future has come true after almost a decade.

This paper aims to contribute to the literature in a few ways. First, it is important to revive the staggering interest of microeconomists on cryptocurrency research by employing undervalued publicly available big data sets. Second, a value(ation) theory of cryptocurrencies is useful in order to understand the price dynamics. And third, understanding how different elements of the price, while spanning almost all of the cryptocurrencies, are weighed is a valuable task to uncover.

2. Literature Review

Academic papers on cryptocurrencies, especially microeconomic point-of- view, are still scarce. The majority of the effort seems to come from macroeconomists and financial markets researchers along with computer scientists. Since the price and the nature of the market structure of a cryptocurrency is the primary concern of most of the parties, the relevant line of work should have been micro because of the field's inherent methodological proficiency.

In search of understanding their price, measuring cryptocurrencies' popularity and general informative website traffic statistics like Wikipedia has been considered by Glaser et al. (2014). They look for a matching rise in visits to Bitcoin's Wikipedia page, daily returns and traffic in a selected country's selected popular cryptocurrency exchange. As an example for previous comments, this approach is inherently false due to the fact that the intellectual nature of obtaining information on Bitcoin is not possible to be linked to a specific exchange's records. Nor they could assert any proof of such linkage in the conclusion. Zhang & Wang (2020) assert that there is a causality between investor attention and returns, also utilizing a similar general data from Google Trends as popularity measure. The paper, on the other hand, provides a good summary of the literature on cryptocurrency literature in economics and mostly finance. Shen et al. (2020) provide a three-factor pricing model by utilizing time series of 1700 cryptocurrencies of different sizes. Finally, Urquhart (2018) finds that general online attention does not affect Bitcoin price.

Shorish (2019) proposes a hedonic modeling for cryptocurrencies. Sparking motivations for the paper at hand, the mentioned paper models the buyer's and seller's problems of utility and profit maximization, respectively, in a classical sense. Here, a unique big data set will be utilized in an empirical framework to break down elements of price, in the footsteps of the original paper by Rosen (1974).

As a general conclusion about the literature at hand, the limited data availability makes it easy to ignore theoretical concerns on actual relatedness among dependent and independent variables before running through a terminal. This study aims to aid this problem under a directed microeconomic framework.

3. Theoretical Framework

Agents in cryptocurrency market depict an interesting supply and demand structure. A person, or group, comes up with an idea and a project, then publishes online on their own. And with no other requirements or even with no costs, there is a new cryptocurrency born. Standing solely on intellectual and computational skills, the only requirement is to find someone who is willing to pay anything[2] to get yours. The theory of cryptocurrency price stands on community mechanisms and it largely reflects collective movement (Stosic et al., 2018).

The supply comes from mostly anonymous parties, which consists of two groups: one group is creator of the asset, hence generally holding a large portion of the global supply and distributing according to own preferences. Another group of suppliers are contributors who naturally accumulate the asset as they accomplish tasks, namely helping the cryptocurrency's functioning. Finally, cryptocurrency algorithms can be formulated as constant or varying in terms of its supply. It is chosen arbitrarily by the issuer and manipulation in supply can be implemented automatically or manually by the controlling body. Popular formulations of cryptocurrencies include interest payments for farmers or stakers by releasing new supply, or, purging certain amounts of the supply occasionally to promote a scarcity impression irrespective to it being limited- or unlimited-supply. These bulletins of supply manipulations can be coined as tokenomics and such manifests are written and read by parties which mostly lack adequate, if any, knowledge economics. There are buyers in the market that pay for it and get some for whatever use, e.g. hold as a speculative asset, use to buy other things, transfer some value to a third-party etc. Among buyers, there is a group which can be considered as consumers who get some of the cryptocurrency just to store (and possibly lose after a while[3]) without any tangible purpose. Having such a niche market structure makes modeling cryptocurrency prices as speculative in itself and a thorny mission.

Table 1: A Snapshot of van Tonder et al. (2019) Data

Data Items	Count
Cryptocurrency (i)	240
Repository (j)	7,014
Time (t)	380 days
Variable	24
N (Repository&day as one entry)	3,013,780

[2] A nice network advantage is that suppliers do not require buyers to pay with real-life money, but they accept other cryptocurrencies as well. In fact, they can only get paid with other virtual coins in most cases. Even if one wants to pay with money, the seller usually cannot have a means to receive it. So, it represents a new buyer's (and also seller's) problem with utility from holding and transferring virtual currency.

[3] 20% of Bitcoin supply is considered lost (Popper, 2021).

4. Data

Several papers, also mentioned earlier, in the literature make use of very large datasets over lengthy periods. Therefore, it is important to note there that the primary concern has been treating the data at hand as inherently adequate just because it exists and is ready to use. Fortunately, Trockman et al. (2019) managed to collect a custom-made data set for their study by actively monitoring periodical GitHub data that has not been stored and only to be captured on sight.

In this study, the big data of cryptocurrencies collected and made publicly available by Trockman et al. (2019) has been used (see van Tonder et al. (2019) for details of the data set). They seem to underestimate the benefits of heterogeneity by making use of the third dimension of their panel data set, i.e. different repositories of each cryptocurrency.

The master file of van Tonder et al. (2019) has been summarized in Table 1. For the study at hand, 8 independent variables has been utilized from the data set which are tabulated and grouped in Table 2 in terms of their significance. Data set contains various kinds of information of 240 individual cryptocurrencies, denoted with *i*, as seen from Table 1. These cryptocurrencies are distributed among 7,014 GitHub repositories, which is denoted with *j*. Time span of the data covers between January 21, 2018 and on February 4, 2019 which is 380 days, denoted with *t*. There are 24 variables in the original data set. Finally, *N* denotes the total number of entries in the master data set, totaling 3,013,780, that each one of them represents a repository at any day.

The variables in Table 2 should encapsulate specific meanings in GitHub terminology. These so-called "GitHub metrics" have been thoroughly analyzed by many scholars and one might get more than enough information regarding their significance in the literature, e.g. Jarczyk et al. (2014). Basically, GitHub users give stars for appreciated repositories, watchers follow updates of projects closely (and might become contributors after a while (Sheoran et al., 2014)). Interested parties can create forks of a project to contribute, or work, on their own ways. Any tangible involvements to a project can be recorded, weekly as *commits_7d* and yearly as *commits_1y*. Global supply, market capitalization (*mcap*) and market capitalization ranking (*mcaprank*) of a cryptocurrency can be obtained from dedicated servers or websites (in this case, from *coinmarketcap.com* (van Tonder et al., 2019)).

Breaking down the functions and/or signals of cryptocurrency metrics is complex due to multilateral nature of the market. Another contribution of this paper is suggesting that grouping of *cryptometrics* based on their function. In this regard, three main groups and 5 subgroups are proposed. Popularity, Maintenance and Competition are considered as main groups of cryptometrics. The first can be divided into three sub-groups: popularity among supply side agents, interests of skilled people (in terms of the computer science) and the general public. Maintenance can be divided into two with respect to the time-span, either short-run or long-run. These aspects are to be reflected in the previously mentioned and tabulated variables.

Table 2: Proposed Categorical Representation of the Variables

Group	Sub-group	Variable
Popularity	Supply side	watchers, supply
	Skilled	stars
	Public	mcap rank, mcap
Maintenance	Short-run	commits_7d
	Long-run	commits_1y
Competition	-	forks

5. On the Distributional Properties of the Variables

5.1 Kernel Density Estimations

The first step on surveying statistical properties shall start with visualization of data points. Kernel density estimation delivers a general picture of the distribution. Although a snapshot does not prove any definite distributional shape, time-varying plots can provide insight. Figure 5.1 depicts kernel density estimations of the variables used throughout the analysis. It is evident that there are significant differentiation between variables in terms of their variation through time. While the distribution of some of the variables, i.e. watchers, stars and forks, have been interestingly stable during this period, others, i.e. price and *marketcapitalization* (which are obviously mathematically related) have seen drastic changes. This suggests that there can be important stylized facts to be discovered through detailed statistical analysis of the variables.

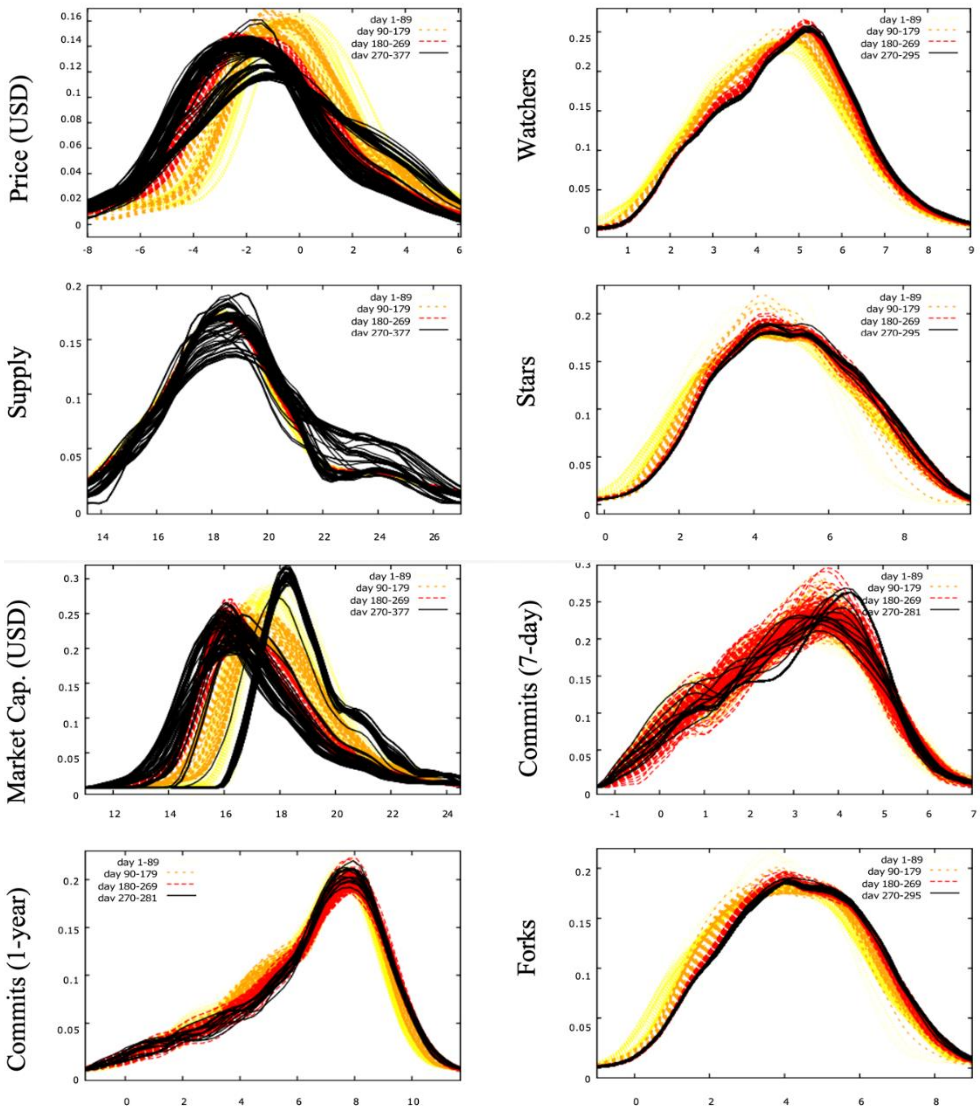
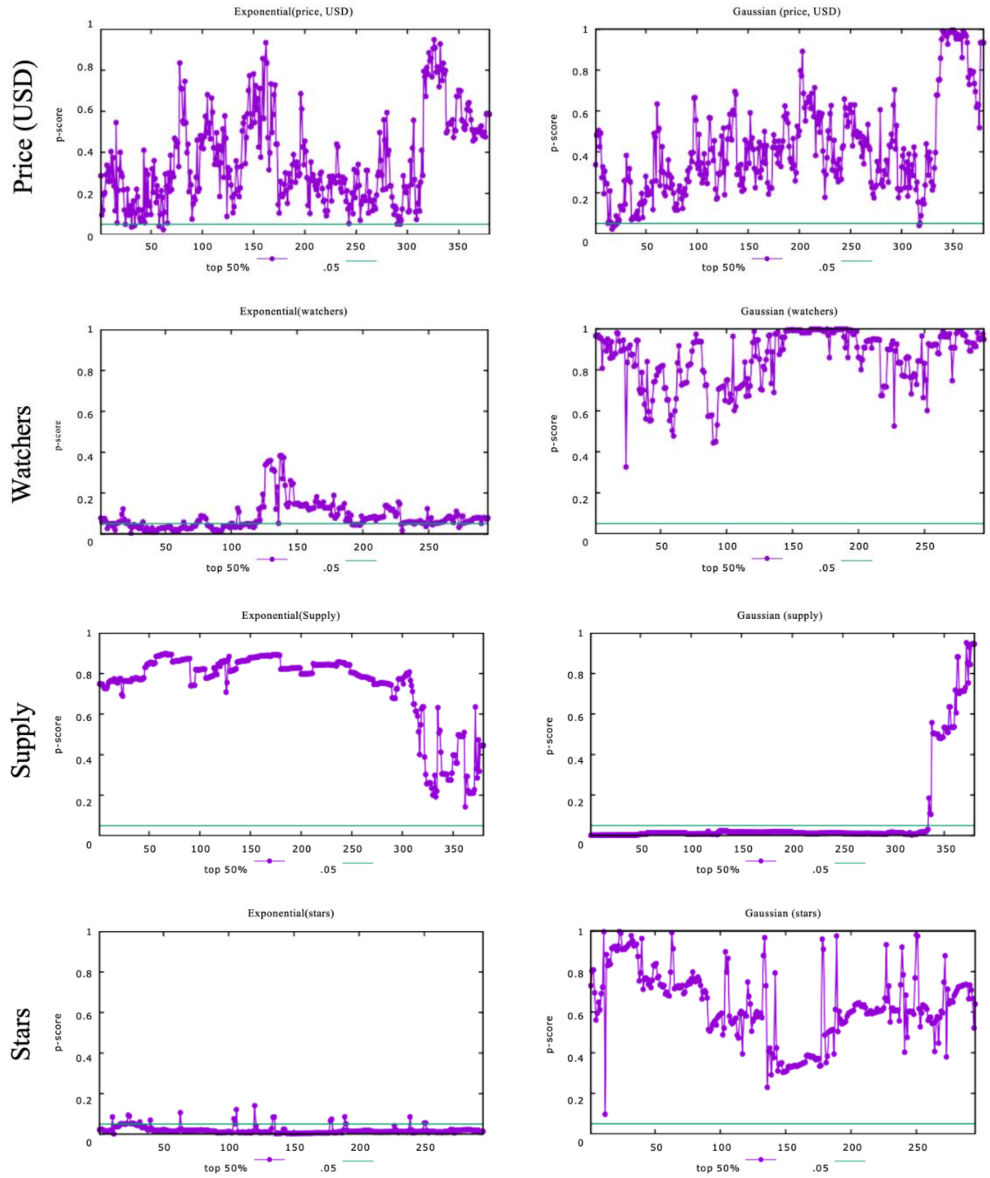


Figure 5.1: Kernel density estimations of the dependent and independent variables. Each line represents a single day, between January 21, 2018 and February 4, 2019 with varying gaps depending on the variable.


Price (USD)
Exponential(price, USD)
Gaussian (price, USD)
Watchers
Exponential(watchers)
Gaussian (watchers)
Supply
Exponential(Supply)
Gaussian (supply)
Stars
Exponential(stars)
Gaussian (stars)
p-score
top 50%
.05

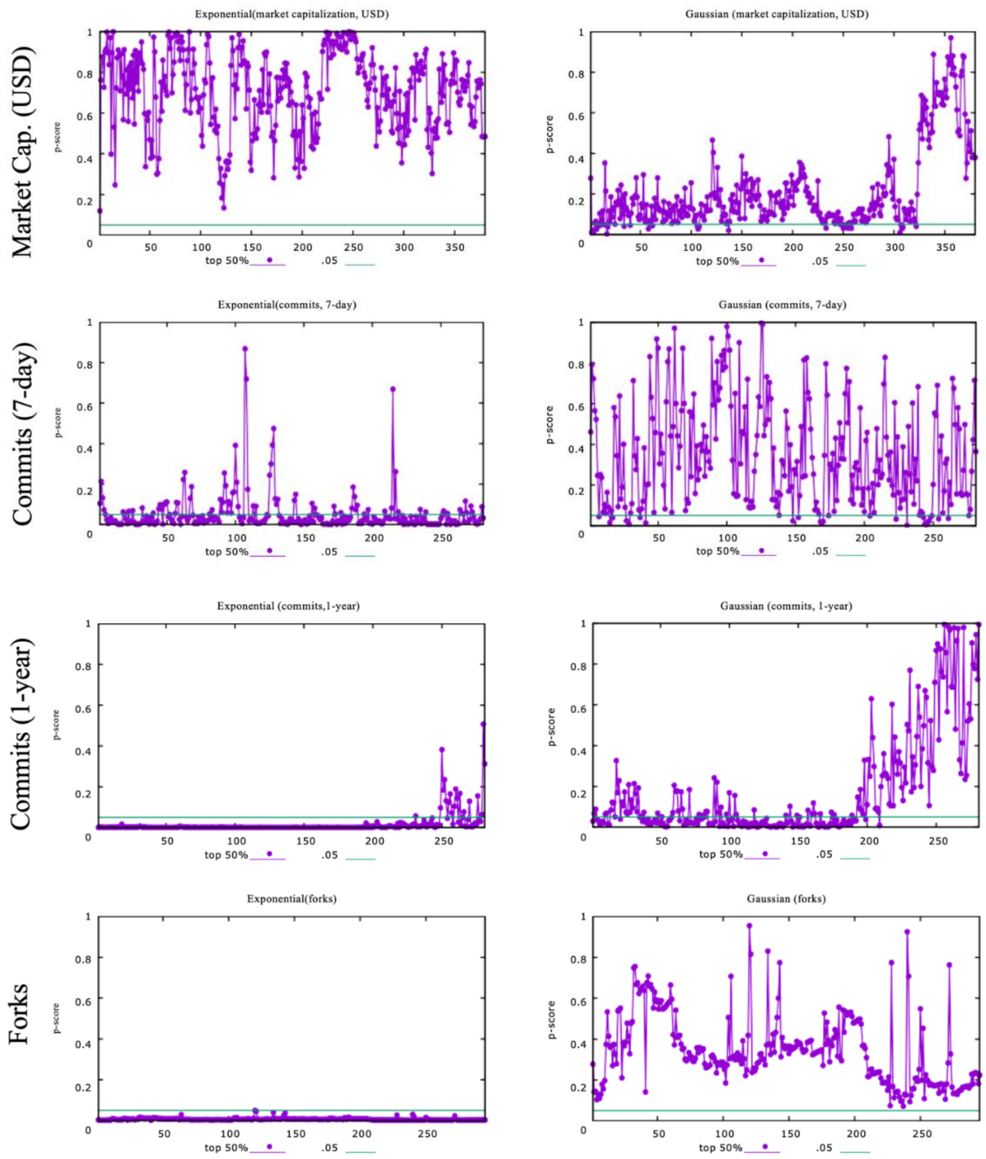


Figure 5.2: GoF of Exponential and Gaussian distributions on related variables. Associated *p-score* is the acceptance rate obtained from KS test for uniformity of the transformed observations (see Aydogan et al. (2022) for further details on the methodology). Each dot represents a single day, between January 21, 2018 and February 4, 2019 with varying gaps depending on the variable.

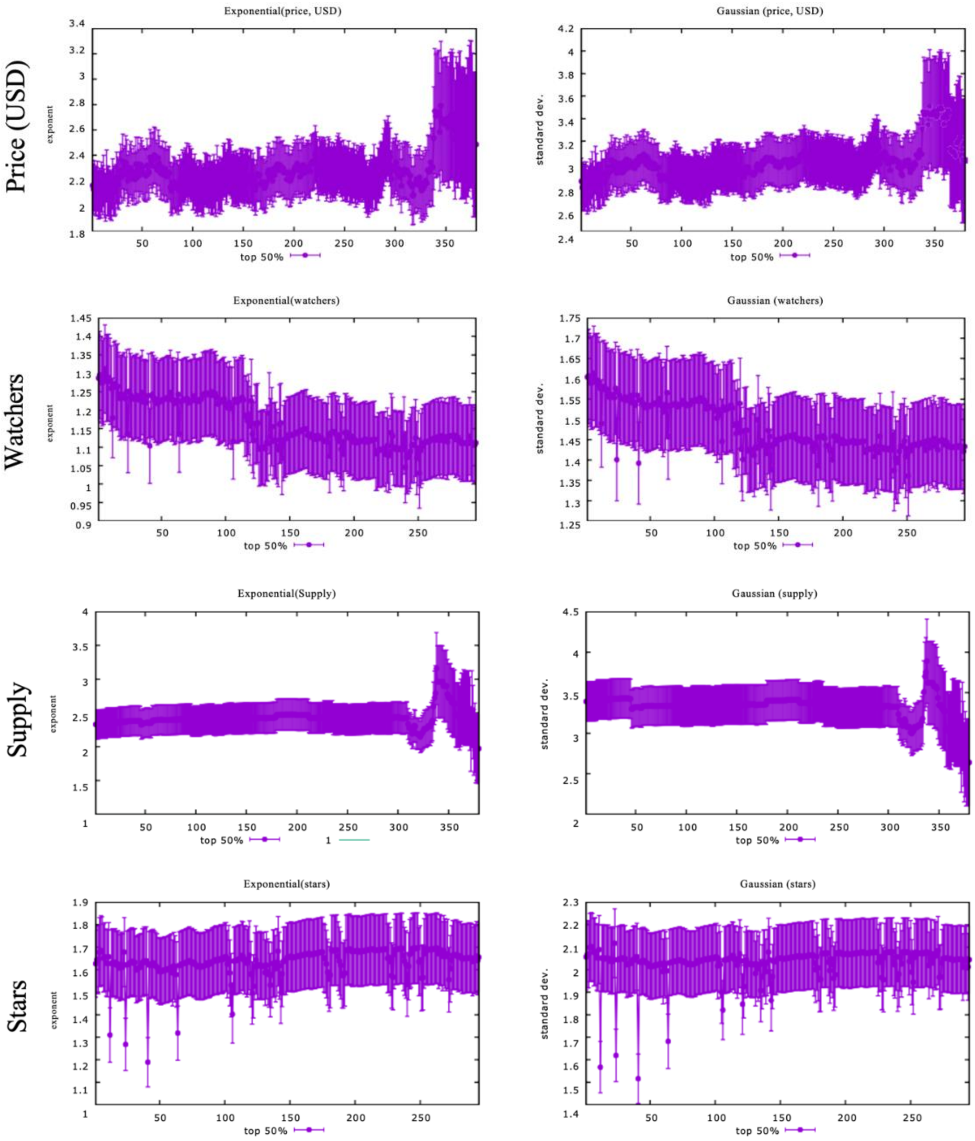
5.2 Testing Distributions: Exponential Against Gaussian

A novel approach to the research on cryptocurrencies could be the distributional analysis of price and its elements. Investigations on the stylized facts of economic and financial variables have deep roots in the economic literature, starting from Pareto (1886) and Gibrat (1931), and highly disputed in terms of both detection and resulting implications[4]. Empirically, the quest comes down to successfully validating the resulting distribution of a variable in terms of whether it provides a good fit for a power law or lognormal distribution, in the tail. In other words, labeling the distributions of cryptocurrency variables (in logarithms) as exponential or Gaussian is an important achievement. In this part, the methodology has been derived from Aydogan et al. (2022) and Goodness of Fit (GoF) statistics for the two competing distributions using Kolmogorov-Smirnov (KS) test are reported in Figure 5.2.

Figure 5.2 suggests that *watchers*, *stars*, *commits_7d* and *forks* can be labeled as Gaussian in the tail, also strongly rejecting the exponential in most of the time. Dollar *price* of the cryptocurrencies return a varying daily layout. However, the power of the method in discriminating between the two distributions improves towards the end of the observed period and Gaussian distribution becomes significantly more probable. On the other hand, supply of the cryptocurrencies are definitely not Gaussian distributed and exponential distribution provides a good fit in the tail. The observed distribution of *commits_1y* had been mainly rejected both in terms of exponential and Gaussian, but it starts to definitively favor Gaussian after a certain time period. To sum up, there are stable and emerging distributional properties among variables through time, which are important to be noticed before conducting further analyses.

Figure 5.3 depicts daily estimations of exponential and Gaussian distribution parameters for the variables in consideration. The importance of the validation method utilized in the previous subsection can be seen here clearly. For instance, if one would only estimate the exponential distribution parameters, it could even be mistakenly concluded that watchers, *commits_7d*, *commits_1y* obey Zipf's law. However, they are shown to be not exponentially distributed.

[4] For a brief introduction, please see Kalecki (1945), Luttmer (2011) and Gabaix (2011).



Price (USD)
Exponential(price, USD)
Gaussian (price, USD)
Watchers
Exponential(watchers)
Gaussian (watchers)
Supply
Exponential(Supply)
Gaussian (supply)
Stars
Exponential(stars)
Gaussian (stars)
exponent
standard dev.
top 50%

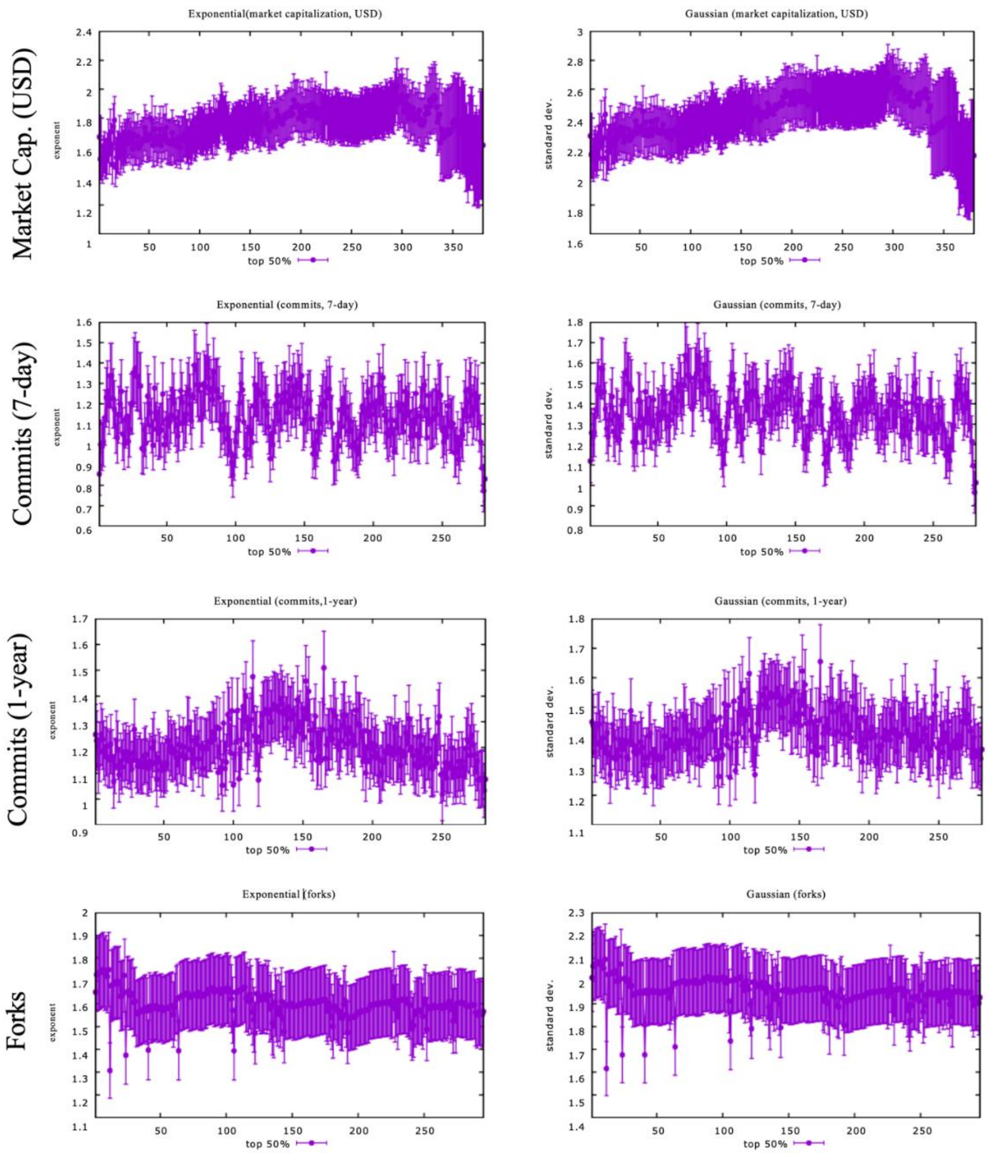


Figure 5.3: Parameter estimations of Exponential and Gaussian distributions. Each dot represents a single day, between January 21, 2018 and February 4, 2019 with varying gaps depending on the variable.

6. Model

Hedonic price theory focuses on the notion that utility from consuming a heterogeneous good depends on its attributes. The final price is a combination of all specs and each attribute has a computable impact. Here, the effect of Popularity, Maintenance and Competition will be measured on cryptocurrency prices using a two-dimensional fixed effects model.

In matrix notation, the transformed model of fixed effects can be shown as:

$$y = D\theta + F\psi + X\beta + s \qquad (6.1)$$

where D is an individual effects matrix sized as $N^* \ x\ N$, X is a $N^* \ x\ P$ matrix consisting time-varying features and F captures the so-called *firm effects* and sized as $N^* \ x\ J$ (Abowd et al., 1999). In this case, N^* denotes repository-time combinations, just over 1.6 million units. N is number of cryptocurrencies in the data, equals to 240. P is 8, including previously mentioned independent variables. Finally, J is the number of repositories in the data, equals to 6,807.

7. Empirical Analysis

The implementation of high dimensional fixed effects models into big data sets have been computationally cumbersome. Here, the method and tools proposed by Cornelissen (2008) will be utilized. One of the many useful features of the three-dimensional linear estimation is the further utilization of heterogeneity and interconnectedness metrics (or repositories in this case).

7.1 Pre-Estimation Analysis

An important aspect of the two-dimensional fixed effects model is that it relies on the presence of movers, or interconnected elements, in order to work better (Cornelissen, 2008). Table 3 presents the dispersion of cryptocurrency repositories, relative to their companions. There are only 19 cryptocurrencies which has a single repository in the data. 5,325 repositories are employed by cryptocurrencies which have more than 100 already. It makes up 78.23 percent of the sample which promotes the appropriateness of the current method.

Table 3: Dispersion of Repositories Among Cryptocurrencies

Multi-repository Cryptocurrencies	Freq.	Share	Cumulative
0 (single repository)	19	.28	.28
1 - 5	122	1.79	2.07
6 - 10	171	2.51	4.58
11 - 20	176	2.59	7.17
21 - 30	105	1.54	8.71
31 - 50	278	4.08	12.80
51 - 100	611	8.98	21.77
> 100	5,325	78.23	100.00
Total	6,807	100.00	

7.2 Trends Among the Variables

As the main driving force of cryptocurrency prices turned out to be their popularity, an interesting quest would be depicting the variables altogether in order to look for any patterns. Figure 7.1 represents the same data in two different layouts to promote tractability. Top 10 cryptocurrencies, ordered in terms of supply and market capitalization, is chosen to present means of stars/watchers ratio, logarithm of supply and logarithm of market capitalization. It reveals that there is no straightforward relation among the variables: left panel does not support any claims on the market capitalization being associated with the supply of the cryptocurrency. Right panel of Figure 7.1 shows that there is no certain relationship between which type of popularity contributes to overall market cap. in the end. There is no clear-cut separation between supply side or skilled popularity in terms of their final value added to the market cap.

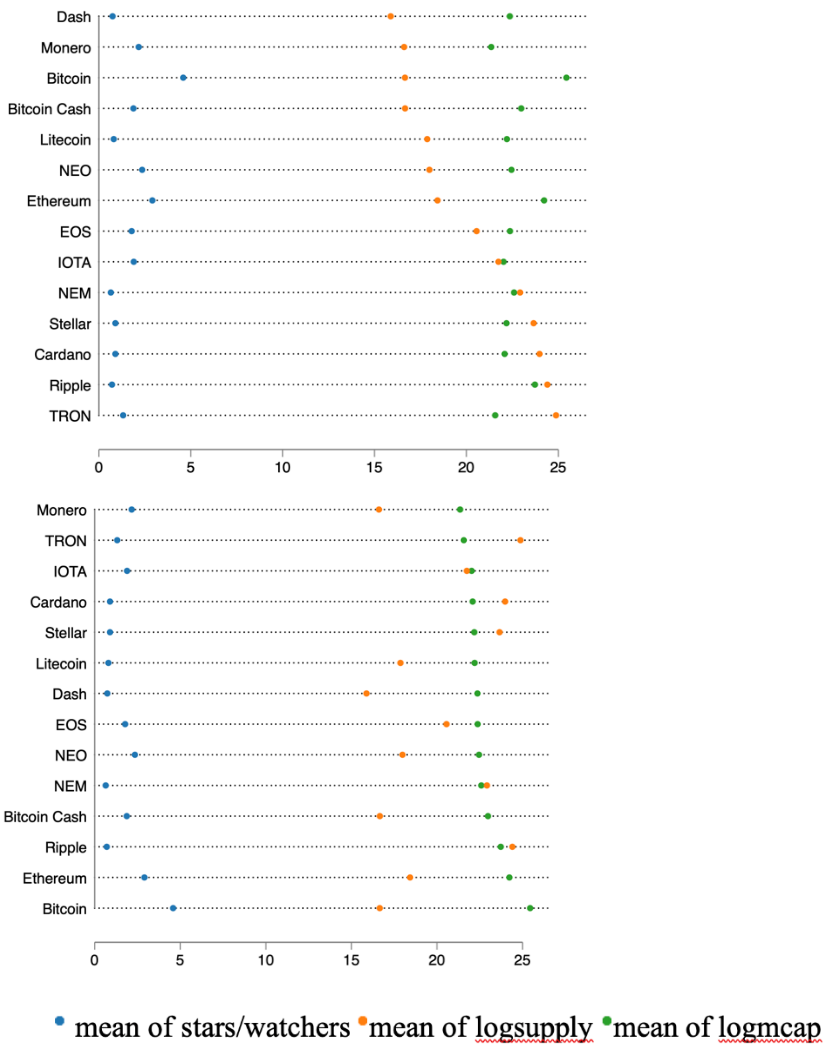


Figure 7.1: Mean of Stars/Watchers ratio along with supply and market capitalization of top 10 highest market cap. currencies. Left panel is sorted by supply, and right panel is sorted by market cap.

7.3 Estimation Results

The output of linear estimation of two-dimensional fixed effects model from Eq 6.1 is presented in Table 4. The popularity measures proposed here turns out to be having varying effects on price. It can be seen that *watchers*' impact on price of a cryptocurrency is almost ten times of the *stars* and *mcaprank*. We can infer from the results that each 2 *watchers* on GitHub adds to a cryptocurrency's price a dollar, while 20 *stars* deliver the same outcome. Also, getting 20 steps up on the market cap ranking (*mcaprank*) of a cryptocurrency impacts its price by a dollar, too. On the other hand, one percent increase in the supply (*logsupply*) of a cryptocurrency makes its price go up by 5.7 dollars, and one percent rise in its market capitalization (*logmcap*) brings its price up by 29.3 dollars. In terms of maintenance, short-term activities on repositories have a sizable impact on cryptocurrency price. Approximately 11 commits to a project over a week would mean a dollar increase in price, via *commits_7d*. Conversely, long-term activity in repositories have almost no price return, the estimated co-efficient of *commits_1y* is 0.001. Finally, competition over the project handling in GitHub, reflected via *forks*, have a considerable negative impact. The price of a cryptocurrency might decrease by a dollar after every two additional forks to a project emerges.

Table 4: Estimation Output

Independent Variables	y = price (US$)
watchers	.551
logsupply	5.747
stars	.052
mcaprank	.049
logmcap	29.364
commits_7d	.087
commits_1y	.001
forks	-.417
N	1,634,544
Fteststat	1,170.2
Ftestprob	0.000

Note: All coefficients are significant with p<0.01

8. Conclusion

When it comes to understand the price dynamics of cryptocurrencies, researchers and professionals tend to over-value its prospects and take the major forces as independent, market oriented and natural. However, it should be noted that a financial instrument-or asset-, while still being in its early periods of life with zero-to-none national or international regulations in place, needs to be treated with its shortcomings. The empirical analysis conducted in this paper lays out that cryptocurrency prices are largely driven by the suppliers' actions and certain basic marketing achievements.

In terms of Popularity, interest from supply side parties have more influence on the cryptocurrency prices than all others. It can be inferred that the cryptocurrency market mostly relies on the interest from producing parties. On the other hand, general public interest and attention from skilled people have similar returns for a cryptocurrency.

Long-term maintenance of a cryptocurrency project returns nothing in terms of price, and short-term developer activity contributes significantly. Therefore, it can be said that cryptocurrencies are not being considered as a long-term investment, or a store of value, by the buyers. Moreover, the Competition among suppliers, or contributors, make the project lose value in the market. This finding might indicate that a perfection or brilliance is important for a cryptocurrency project and market participants try to avoid controversial ones.

Further research might focus on interactive choice mechanisms under buyer's preferences, considering the paying structure for the initial purchase. Also, differentiating supply side participants with their contribution in terms of effort is crucial. With booming number of cryptocurrencies in recent years, it can be interesting to compare the returns on issuing a new cryptocurrency over taking part in live projects.

In terms of further statistical consideration, supplied distributional properties and stylized facts on the cryptocurrency prices and related variables shall provide an important benchmark. New big data collections shall be compared and analyzed based on these findings regarding Gaussian and exponentially distributed variables. Computational price or market behavior models can benefit such identifications, setting viable and sound assumptions on related phenomena.

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