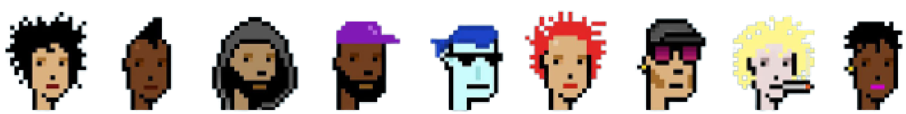


LooksRare and Coinbase NFT Marketplaces: User Growth As A Probability Model

Executive Summary

LooksRare and Coinbase NFT are both NFT platforms launched in 2022 after the crypto bull market that began in 2021. Their user bases grew rapidly as consumers sought out easy-to-use exchanges to buy and sell NFTs. This analysis aims to understand that growth better. There are two key questions I will be answering:

1) What is the best model to represent user growth, particularly for these two NFT exchanges?

2) What comparisons can we make about the customer bases that gravitated towards LooksRare and Coinbase? In particular, is one more heterogeneous, more sensitive to large-scale crypto events, or influenced by marketing?

The model chosen to represent the user growth of LooksRare was a Gamma-Weibull model with 1 covariate that represented the Terra-Luna crash. The model chosen to represent the user growth of Coinbase NFT was a Gamma-Weibull model with 2 covariates that represented ETH trading volumes and number of tweets from @Coinbase_NFT.

The general comparisons between the customer bases are as follows: users of LooksRare appear to be less heterogeneous, more sensitive to crypto events, and less influenced by marketing when it comes to adoption.

Introduction

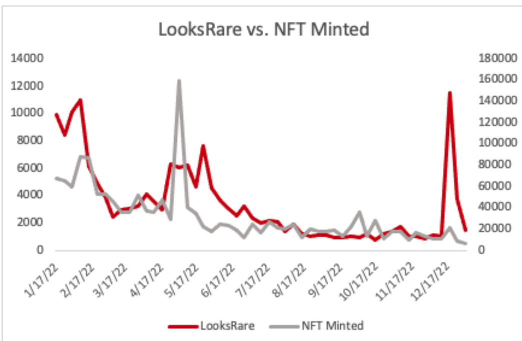
LooksRare and Coinbase NFT both entered the NFT marketplace landscape in early 2022, in January and April respectively. Coming off the heels of a year that saw crypto markets explode with growth, both these companies were looking to capture the vast customer base of NFT aficionados that participate in buying and selling NFT activities.

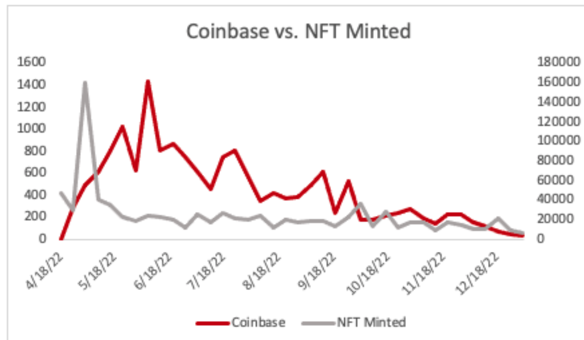
LooksRare was the newer company with little brand power but a strong application and earlier launch. Coinbase NFT was the extension of parent company Coinbase, the largest centralized exchange for cryptocurrencies in the United States. Given these distinct profiles, it would seem reasonable that both companies would attract customer bases with different characteristics. Being able to identify these characteristics is hugely beneficial from a marketing standpoint - knowing what sits well with your potential customers and leads to user adoption is critical for scaling a product.

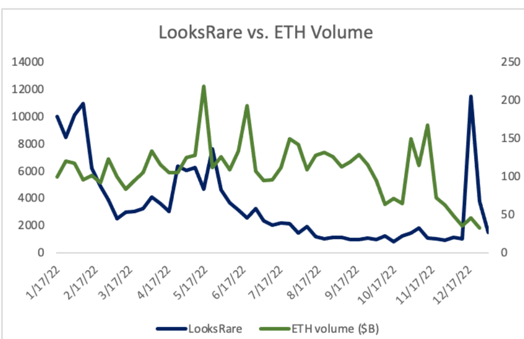
Data

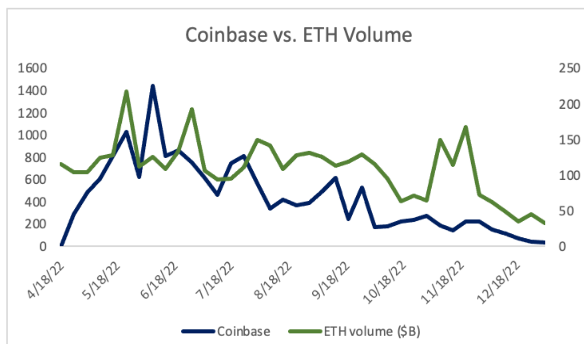
The given data describes the number of unique wallet addresses (users) that joined LooksRare and Coinbase at the end of every week until 1/2/2023. This data was obtained from Dune Analytics. The rest of the given data shows NFT mint activity obtained from Nansen and Ethereum (ETH) trading volume in $Bn obtained from Yahoo Finance.

Note that Coinbase launched in April and thus doesn't have any data before the week that ended on 4/25/2022.









LooksRare's customer growth seems to follow NFT mint activity but with a lag and muted effect. It does not seem to be correlated with ETH trading volume. Coinbase's customer growth seems to follow NFT mint activity roughly with a lag of a bit more than a month, but the effect seems more pronounced than LooksRare's. ETH volume seems to track Coinbase NFT user adoption well and may be a good covariate to explore.

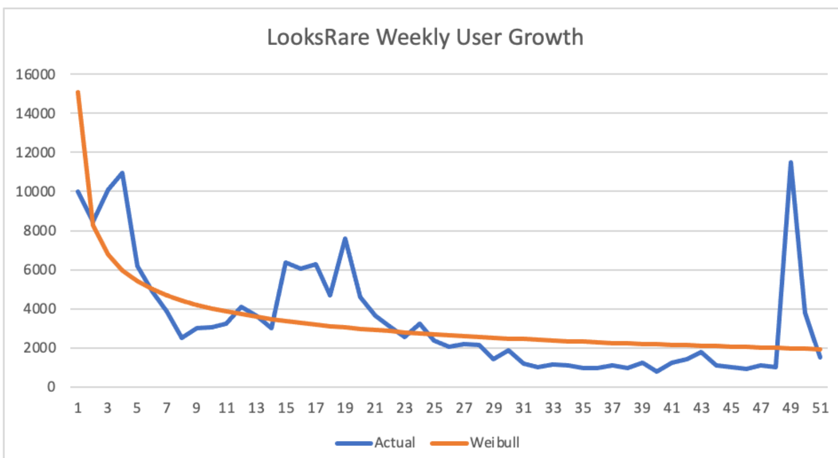
Overall, LooksRare's and Coinbase NFT's growth patterns do not seem that similar. There's a relative spike for both growth lines in May although it's relatively larger for Coinbase. After May, both growth lines taper off but LooksRare's spikes back up before falling back down at the end of 2022.

Model Selection

The selection process utilized various models that added heterogeneity, duration dependence, and covariates to the picture until the model felt sufficiently representative. In total, 17 models were created to determine the best one for LooksRare and Coinbase NFT. The following will explore that journey and highlight some of the more interesting models. A maximum likelihood estimation was the primary factor for choosing one model over another, but as I detail the exploration other metrics for model selection will also be utilized.

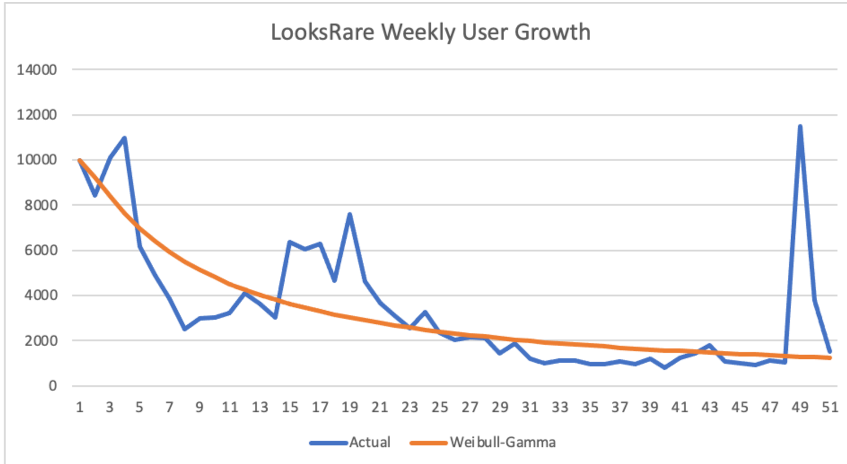
LooksRare: Weibull-Gamma, 1 covariate

First I considered a Weibull model because it utilized duration dependence. This situation involving customer growth over time invites time dependence, and thus I felt comfortable using the Weibull model as a starting point. Since the Weibull distribution assumes that all customers share a common propensity (lambda) to join LooksRare, this initial model assumes no heterogeneity in the underlying latent value.



Lambda = 0.015 | c = 0.637 | MAPE = 53% | BIC = 1,904,221

While this was a decent start, I wanted to incorporate a mixing model that could provide heterogeneity to the underlying propensity to join LooksRare. This brought me to the Weibull-Gamma model.

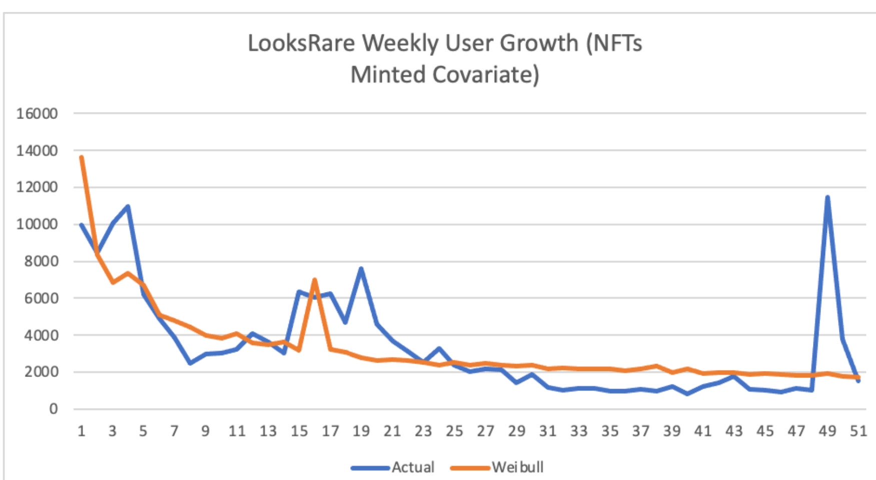


r = 0.082 | alpha = 7.741 | c = 1.084 | MAPE = 39% | BIC = 1,877,188

Introducing heterogeneity to the underlying lambda value seemed to have a positive effect on the model. The in-sample MAPE decreased to 39%, and the visual fit seems more palatable. I also conducted an Likelihood Ratio Test to see the significance of the change and obtained a p-value of 0, making me feel comfortable to settle with the Weibull-Gamma model.

Model	**Total LL**	**BIC**	**MAPE**
Weibull	-952,096	1,904,221	53%
Gamma-Weibull	-938,580	1,877,188	39%

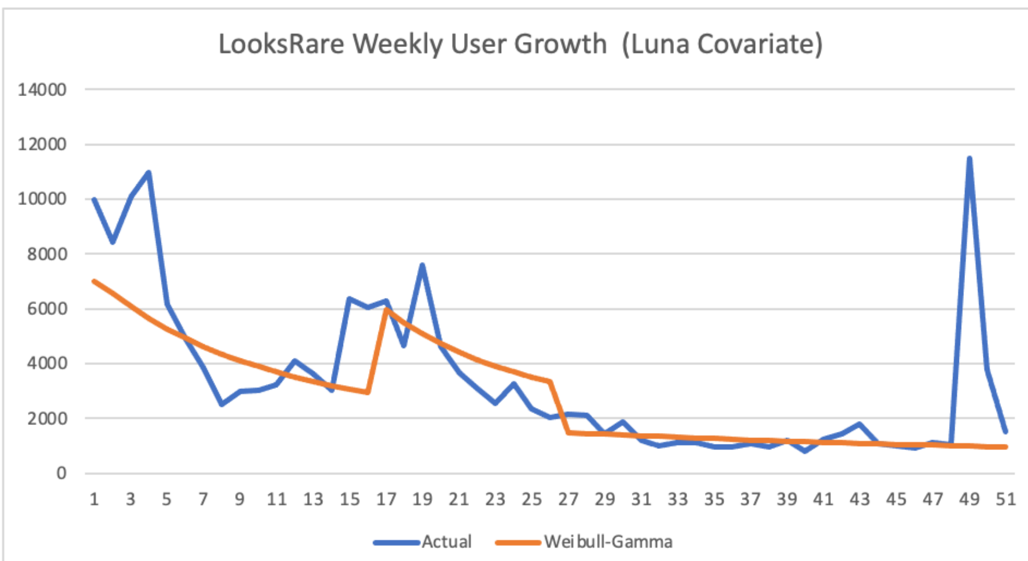
From the initial data analysis, LooksRare appeared to have a correlation with NFT mint values but not ETH trading volume. This prompted me to add NFT mint activity as a covariate.



r = 0.099 | alpha = 11.791 | c = 1.010 | MAPE = 39% | BIC = 1,876,138 | b(NFT_minted) = 0.351

While there seemed to be a visual improvement from adding the NFT activity covariate, it hardly improved the total LL and had no effect on the in-sample MAPE. The lack of improvements were not a result of choosing the wrong covariate either, adding in ETH trading volume as a covariate both in addition to NFT activity and as a sole covariate failed to improve model performance.

At this point, I began to consider the possibility of other covariates. Despite the NFT activity covariate not improving model performance, the model did not reject the covariate and solver returned a b(NFT_minted) value of 0.351. The visualization also supported the theory that NFT mint activity was correlated to user adoption for LooksRare. My hypothesis was that potential customers of LooksRare were more in touch with the crypto world given that NFT mint activity affected their adoption. These customers would also be influenced by large-scale events in the crypto world like the Terra-Luna crash. Thus, I decided to implement the Terra-Luna crash as a boolean covariate, 0 for before the crash, and 1 for the weeks the crash was relevant (to determine when the crash was relevant, I utilized Google Trends and a supplementary graphic can be found in Appendix A).



r = 0.081 | alpha = 10.966 | c = 1.018 | MAPE = 27% | BIC = 1,873,037 | b(Luna) = 0.767

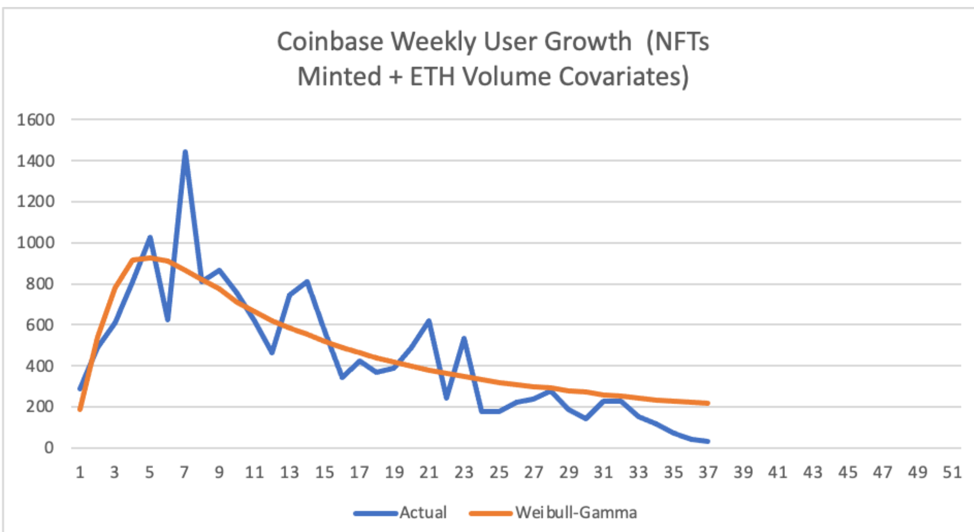
This model was a significant improvement on the MAPE and total LL (which can be found in Appendix B). Interestingly, a model that incorporated the other two covariates NFT mint activity and ETH trading volume actually would reject trading volume as a covariate and only include NFT mint activity and the Luna crash as covariates. The in-sample MAPE for that model was the lowest MAPE I received, being 22%, however the out-of-sample MAPE was 32% which was higher than the model listed above.

All things considered, I felt this model best captured the LooksRare growth line.

Coinbase NFT: Weibull-Gamma, 2 covariates

The initial part of the Coinbase model selection began the same as LooksRare. I tried a Weibull model to start with given the duration dependence that is embedded in any consumer adoption curve. I then added heterogeneity using a Gamma-Weibull model and saw significant improvements. Visuals and parameters of the models can be seen in Appendix C.

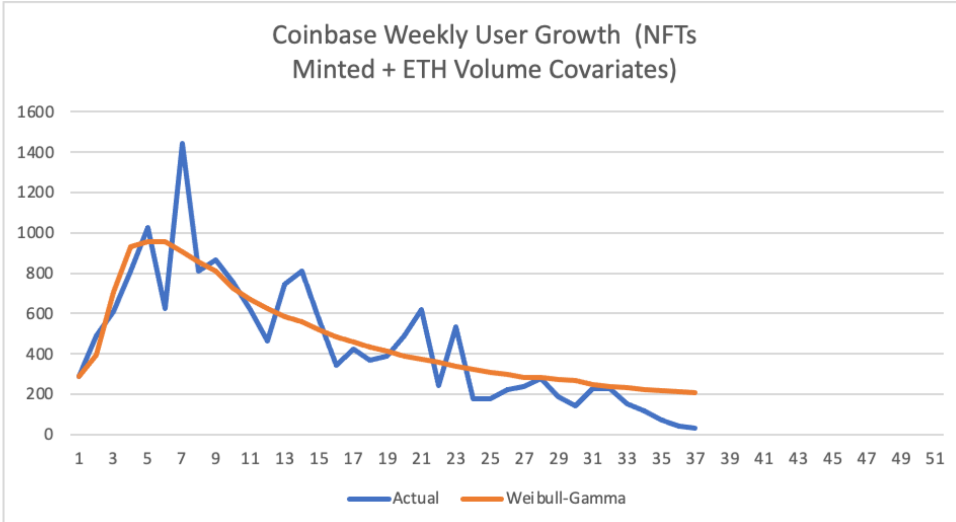
My first instinct was to add the ETH Volume covariate to the model given the strong visual indication that there was a correlation. Coinbase users who trade ETH and other crypto assets on the main Coinbase platform are also more likely to discover another Coinbase product while using Coinbase products, meaning adoption of Coinbase NFT during periods of increased ETH trading volume checks out.



r = 0.004 | alpha = 21.403 | c = 2.052 | MAPE = 30% | BIC = 266,230 | b(ETH_Volume) = 0.184

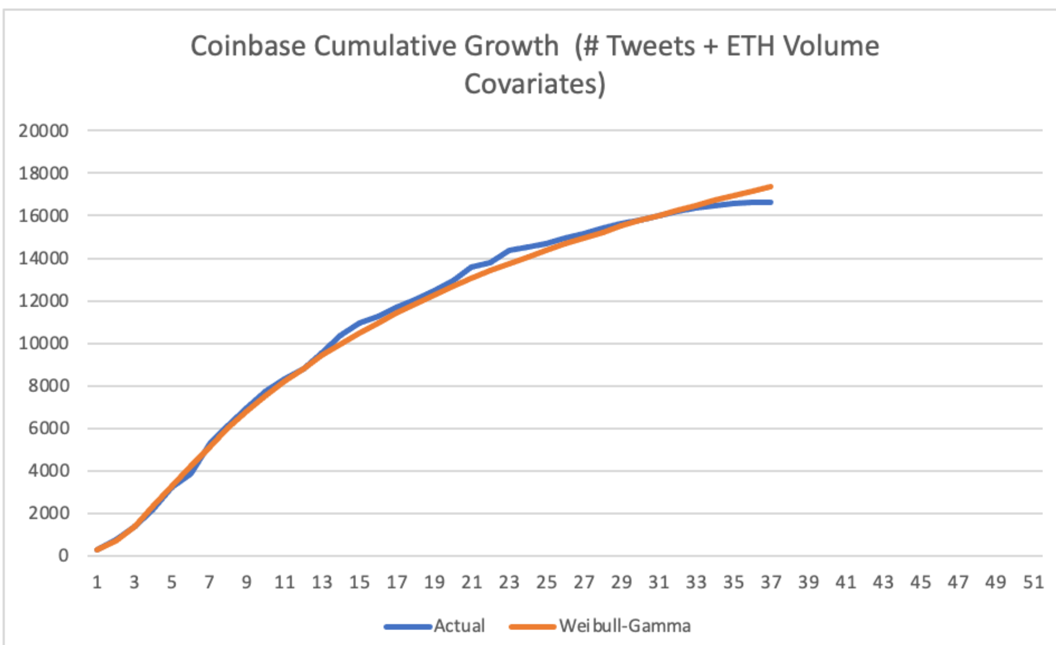
Additionally, trying out the mint activity covariate only led to it being rejected by Solver (see Appendix D). This confirmed that ETH Volume was the more relevant covariate.

I felt that there must be another covariate that may improve the model quality. I was curious to see how direct marketing from the Coinbase NFT Twitter account affected user adoption. The intuition was that Coinbase was already an established brand that likely saw a lot of user adoption being channeled through Twitter. After counting the amount of tweets with over 50 likes from @Coinbase_NFT every week and adding it to the model as a covariate, the results were surprising.



r = 0.003 | alpha = 33.471 | c = 2.487 | MAPE = 27% | BIC = 266,114 | b(ETH_Volume) = 0.429 | b(#_tweets) = 1.010

In-sample MAPE decreased notably, the fit improved significantly, and overall more of the story is being told. The cumulative growth function further shows the quality of fit.



Interestingly, the model fit remains roughly the same with or without the ETH Volume covariate, showing how strong the #_Tweets covariate really is. Appendix E shows the parameters for both models.

Conclusions

Summary Metrics

	r	alpha	c	b(Luna)	b(ETH_Volume)	b(#_tweets)
LooksRare	0.081	10.966	1.018	0.767	-	-
Coinbase	0.003	33.471	2.487	-	0.429	1.01

Performance Metrics

	In-sample MAPE	**Out-Sample MAPE**	**LL**	**BIC**
LooksRare	27%	27%	-936,505	1,873,037
Coinbase	28%	187%	-133,048	266,123

Comparisons Across Customer Bases

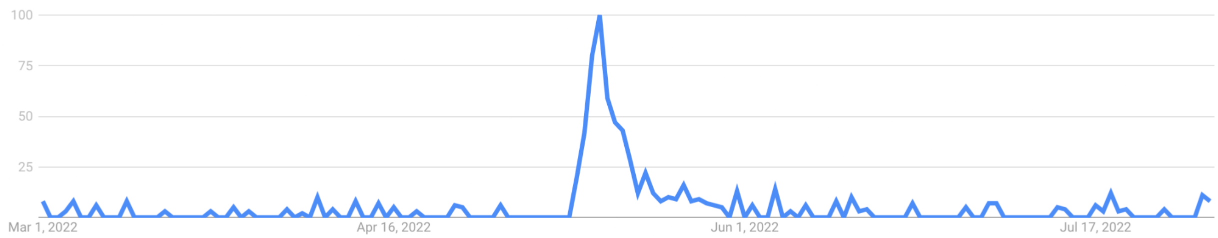
1) Coinbase has the more heterogeneous customer base. This makes sense given their large brand reach. The managerial conclusion here would be to rely on marketing that is friendly towards a wide-variety of audiences. LooksRare would most likely be able to conduct marketing that is targeted at more crypto savvy customers.

2) LooksRare customer adoption is less driven by Twitter marketing than Coinbase customer adoption. As seen in Appendix E, the number of tweets was hardly a significant covariate for the LooksRare model. On the other hand, the Coinbase final model was heavily influenced by the amount of tweets they put out. For Coinbase customers, Coinbase tweets likely carry significant weight given their familiarity with the brand. Announcements, engagement, and any random post could all serve as the top of the funnel for customer adoption.

3) LooksRare customer adoption is more influenced by large-scale crypto events. LooksRare's final model is heavily influenced by the Terra-Luna crash covariate. This checks out as well, given that LooksRare's customer base may be more hard-core crypto enthusiasts who hopped on the first launch and distrust Coinbase's centralized approach (LooksRare is also centralized but does not have the same reputation).

Overall, despite the differences in customer bases, both groups ultimately are best modeled with a Gamma-Weibull distribution. There are ways to improve this model, as evidenced by the high out-of-sample MAPE's for Coinbase and high MAPE's in general. Future iterations of this analysis could make more use of latent-segmentation, and other underlying model changes, instead of focusing on covariate analysis.

Appendix A:



Interest over time for search term “Luna Crash” (was relevant from weeks of 5/9/22 to 7/11/22)

Appendix B:

Gamma-Weibull Parameters

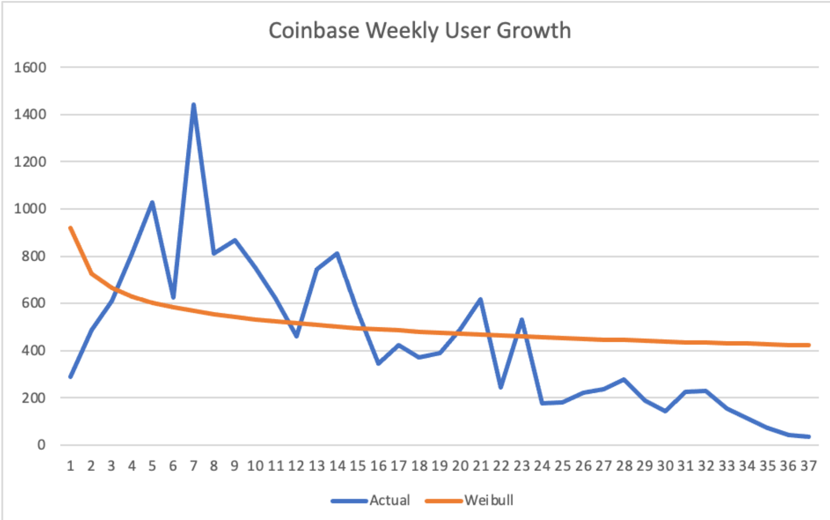
Total Population		1,000,000		In Sample			**BIC**	1877188.01
r		0.0824		**MAPE**	39%			
alpha		7.7409		Out of Sample				
c		1.0383		**MAPE**	36%			
sum LL		-938580						

Gamma-Weibull with Luna Covariate Parameters

Total Population		1,000,000		In Sample			**BIC**	1873037.82
r		0.08066942		**MAPE**	27%			
alpha		10.9662729		Out of Sample				
c		1.01837358		**MAPE**	27%			
B_NFT_Minted		0						
B_ETH_Volume		0						
B_LUNA		0.76664873						
sum LL		-936505						

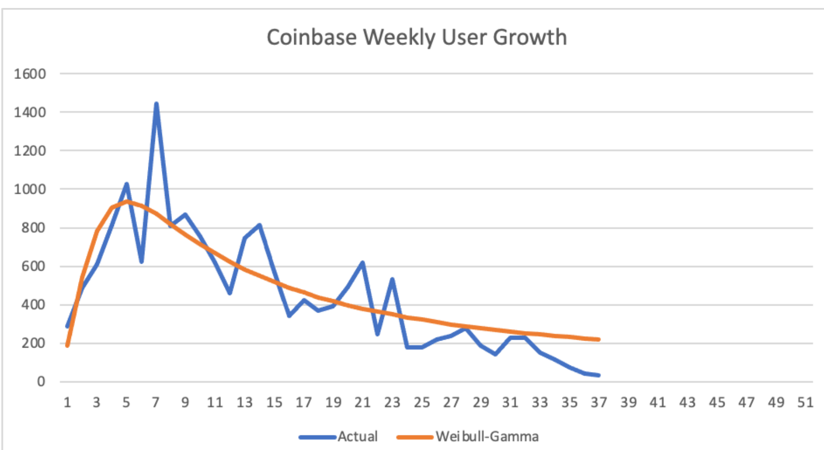
Appendix C:

Weibull



Total Population		1,000,000		In sample				**BIC**	268916
Lambda		0.00092148		**MAPE**	59%				
c		0.83756484		Out of sample					
sum LL		-134444		**MAPE**	450%				

Gamma-Weibull



Total Population		1,000,000		In Sample				**BIC**	266231.301
r		0.0040		**MAPE**	28%				
alpha		20.8505		Out of Sample					
c		2.0553		**MAPE**	196%				
sum LL		-133102							

Appendix D:

Gamma-Weibull with NFT_Minted and ETH_Volume covariates

Total Population	1,000,000	In Sample		**BIC**	266230.7675
r	0.00401797	**MAPE**	30%		
alpha	21.4035783	Out of Sample			
c	2.0521896	**MAPE**	194%		
B_NFT_Minted	0.0001				
B_ETH_Volume	0.18377485				
B_#_Tweets	0				
sum LL	-133102				

Appendix E:

Gamma-Weibull for ETH_Volume and #_Tweets Covariates

Total Population	1,000,000	In Sample		**BIC**	266114.5041
r	0.0031761	**MAPE**	27%		
alpha	33.4706464	Out of Sample			
c	2.48726332	**MAPE**	180%		
B_NFT_Minted	0				
B_ETH_Volume	0.42916194				
B_#_Tweets	1.01008856				
sum LL	-133043				

Gamma-Weibull for only #_Tweets Covariate

Total Population	1,000,000	In Sample		**BIC**	266123.0831
r	0.0031761	**MAPE**	28%		
alpha	33.4706464	Out of Sample			
c	2.48726332	**MAPE**	187%		
B_NFT_Minted	0				
B_ETH_Volume	0				
B_#_Tweets	1.01008856				
sum LL	-133048				

Appendix E:

Gamma-Weibull for LooksRare tweets

Total Population	1,000,000	In Sample		**BIC**	1874819.551
r	0.09805523	**MAPE**	36%		
alpha	17.3669191	Out of Sample			
c	0.99571878	**MAPE**	32%		
B_NFT_Minted	0.3582585				
B_ETH_Volume	3.87995336				
B_#_Tweets	1E-04				
sum LL	-937396				