An Analysis of Gods Unchained Cards' Orders

1 Introduction

I hadn't given much thought to blockchain technology and NFTs since their meteoric rise and subsequent decline in 2021. At the time, the NFT space generated immense buzz, but that momentum quickly faded amid public skepticism, negative press, and a widespread perception that NFTs had failed to establish any meaningful or practical use cases. However, my interest in the space was recently reignited when I came across projects that, surprisingly, are still generating millions of dollars in revenue. This discovery felt almost incomprehensible—how could such significant financial activity persist in an industry that many had written off as obsolete or speculative?

One project that particularly caught my attention is Gods Unchained Cards, a digital collectible card game hosted on Immutable X, an Ethereum-based blockchain platform. Gods Unchained closely mirrors the gameplay of popular traditional card games like Magic: The Gathering or Hearthstone, which are beloved for their strategic depth and trading mechanics. What sets Gods Unchained apart, however, is its blockchain integration. The cards themselves are non-fungible tokens (NFTs), meaning that each digital card has a unique identity and ownership record stored on the Ethereum blockchain. This feature allows players to truly "own" their cards, much like physical trading cards in conventional games.

This ownership model introduces significant advantages for players. In traditional card games, the cards exist solely within the game's ecosystem, and ownership is essentially licensed rather than outright. Players cannot transfer their cards freely, and their collections hold no value outside the game. In contrast, Gods Unchained allows players to buy, sell, and trade their cards on the Immutable X marketplace. This creates a tangible economic layer where cards can accrue value over time, driven by their rarity, demand, and in-game utility. The decentralized nature of the blockchain ensures that transactions are transparent, secure, and not controlled by a central entity.

This economic model is particularly interesting because it transforms the dynamics of collectible card games. Beyond just playing for enjoyment, players can engage in speculation, treating the cards as assets with potential for profit. This speculation mirrors behaviors seen in traditional markets, such as stock trading, where users make purchasing decisions based on perceived future value. At the same time, the integration of blockchain technology introduces a level of permanence and authenticity that was previously unattainable in digital games. Players can trust that their ownership rights are immutable, and the cards' digital scarcity can be verified on the blockchain.

The success of Gods Unchained Cards also highlights the broader potential for blockchain-based gaming. While many NFT projects struggled to find audiences due to a lack of utility, Gods Unchained marries blockchain technology with an engaging, familiar gameplay experience. This approach ensures that the game appeals not only to crypto enthusiasts but also to traditional gamers who value strategic gameplay and ownership of their collections. The fact that Gods Unchained has generated over 470 million to date demonstrates the viability of this hybrid model and suggests that blockchain gaming can carve out a sustainable niche in the broader gaming industry.

From a broader perspective, the success of Gods Unchained also sheds light on the role of Immutable X as an ecosystem. As a layer-2 scaling solution for Ethereum, Immutable X allows for gas-free transactions, which significantly reduces costs for players buying and trading cards. This feature addresses one of the major pain points of blockchain platforms—high transaction fees—and makes participation in the marketplace far more accessible. Combined with its focus on environmental sustainability, Immutable X presents a compelling case for how blockchain can overcome the hurdles that initially limited mainstream adoption.

2 Data Description

The data for this analysis comes from the live API provided by `https://immutascan.io/`, a platform that tracks activity across the Immutable X blockchain. I focused on two key endpoints for this project. The first is the deposits endpoint, which tracks the deposits made by users across the entire marketplace. The second is the orders endpoint, which provides detailed data on successful trades specifically for the Gods Unchained Cards collection. By focusing on these two endpoints, I was able to capture user behavior both in terms of overall deposits and specific purchase activity.

Due to the restrictions of the Immutable X API, there were a few challenges with data collection. First, the API does not allow for real-time data streaming or polling. Instead, data must be fetched manually by repeatedly querying the API. Second, obtaining an API key, which would streamline access, requires business partner status, which I was unable to secure. To overcome these limitations, I opted to collect data for a fixed time period: November 2024. This month was of particular interest because the Gods Unchained collection generated 20 million in revenue, marking it as a high-performing period worth analyzing in detail.

The entire process of collecting and preparing the data can be broken into two main stages: extraction/transformation and analysis. I used Python for the former and R for the latter.

For the extraction step, I realized that while the data returned by the API differed depending on the endpoint, the actual logic for interacting with the API was quite similar. In general, the process involved passing an endpoint, supplying a cursor to retrieve new records, and looping through results until the cursor returned a null value. To streamline this, I created a helper class that handled all the API interactions and cursor logic. This class served as a template for other endpoints to inherit from, greatly simplifying the codebase. While I only queried two endpoints in this analysis, the class design makes it easy to add new endpoints in the future with minimal additional code.

As records were fetched from the API, each result was returned as a JSON object. I parsed these objects into Python dictionaries and appended each dictionary to a list as a temporary storage structure. Before finalizing the data, I applied a light transformation step to handle Ethereum (ETH) values. On blockchain systems like Ethereum, financial data is often stored as large integers to avoid floating-point precision errors. However, these raw values are not human-readable, so a decimal value is also provided for calculation purposes. To convert the raw ETH values into a usable form, I divided each value by 10 raised to the power of 18, since the standard scaling factor for Ethereums is 18 decimal places.

Once all the records were collected and transformed, I converted the list of dictionaries into pandas DataFrames. DataFrames provided a clean tabular structure for organizing the data and made it simple to export the results to CSV files. These CSV files were then imported into R for further statistical analysis, model fitting, and visualization.

3 Methods

Initially, I attempted to fit a linear model to understand the relationship between the number of orders placed by a user and their total buy quantity. At first glance, the data appeared to exhibit a positive trend, which suggested that a linear model might be appropriate. However, after fitting the model, it became clear that the assumptions of linear regression were consistently violated. The residuals showed patterns of non-linearity, indicating that the model was failing to capture the underlying relationship in the data. Even when I attempted to employ more complex linear models, such as Generalized Linear Models (GLMs), the results remained inadequate, as these models still imposed a rigid linear structure that did not align well with the data's behavior.

Given these challenges, I turned to a Generalized Additive Model (GAM), which is better suited for data with non-linear relationships. Unlike linear models, GAMs allow for the relationship between the predictors and response variable to be captured through flexible smooth functions. This flexibility enables the model to adapt to the data's inherent structure without being constrained by strict linearity. By employing the GAM, I found that it fit the data much more effectively, as it was able to account for the nonlinear trend that the linear models could not capture.

To further validate the GAM model and assess the reliability of its predictions, I applied a bootstrapping procedure. Bootstrapping involves repeatedly resampling the original data with replacement to generate new datasets. For each resample, the GAM model is refit, and predictions are made. By aggregating the predictions across all the resampled datasets, I was able to calculate confidence intervals, which quantify the uncertainty around the model's estimates. These confidence intervals are particularly useful for identifying regions where the model's predictions are less reliable, such as areas with sparse data or high variability.

In summary, by moving from a linear model to a GAM, I was able to capture the nonlinear relationship between the number of user orders and total buy quantity more effectively. The use of bootstrapping further validated the model and provided a clearer understanding of the uncertainty surrounding its predictions. This approach not only improved the model's performance but also offered more robust insights into the structure of the data.

4 Analysis Results

Starting with exploratory data analysis, I sought to understand the relationship between the number of orders placed by users and the total buy quantity. Much of the data was concentrated in the lower left-hand corner, where both the number of orders and total buy quantity were relatively small. However, as the total buy quantity increased, there was a noticeable upward trend, suggesting a positive relationship between the two variables.

To visualize this relationship, I created a scatter plot of the data.

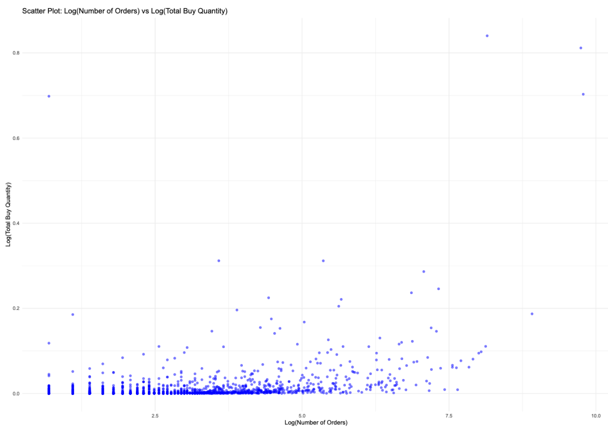

Figure 1: Scatter Plot: Log(Number of Orders) vs Log(Total Buy Quantity).

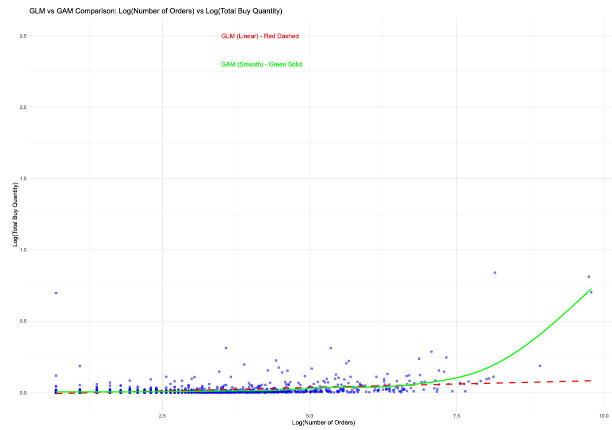

Figure 2: Comparison of GLM and GAM Fits: Log(Number of Orders) vs Log(Total Buy Quantity).

The initial scatter plot revealed a clear positive trend between the number of orders and total buy quantity, but the relationship was not perfectly linear. To address this, I applied a log transformation to both variables. This transformation helped to linearize the relationship and stabilize the variance, making the data more suitable for modeling.

Despite the log transformation, I encountered challenges with fitting a simple linear model. The residuals showed clear deviations from normality, and patterns emerged that indicated the linear model was failing to capture the non-linear nature of the relationship. In an effort to improve the model, I tried increasingly more complex linear approaches, including generalized linear models (GLM). Unfortunately, the GLM still struggled to represent the data effectively, as the assumptions of linearity and homoscedasticity remained violated.

Recognizing that the linear models were inadequate, I turned to a generalized additive model (GAM). Unlike linear models, GAMs use smooth functions to capture relationships that are not strictly linear, making them well-suited for data with complex, non-linear patterns.

The comparison between the GLM and GAM fits is shown in the following chart:

The chart highlights the key difference between the two models. The GLM (red dashed line) attempts to fit the data with a strict linear relationship, which fails to account for the subtle curvature in the trend. In contrast, the GAM (green solid line) captures the non-linear nature of the relationship more effectively by using smooth functions. This flexibility allowed the GAM to better follow the patterns in the data, particularly in areas where the GLM visibly deviated from the observed points.

Ultimately, the GAM provided a much better fit for the data, capturing the underlying relationship between the number of orders and total buy quantity in a way that the linear models could not. This realization led me to proceed with the GAM for further analysis. Here is the fit for the GAM model by itself:

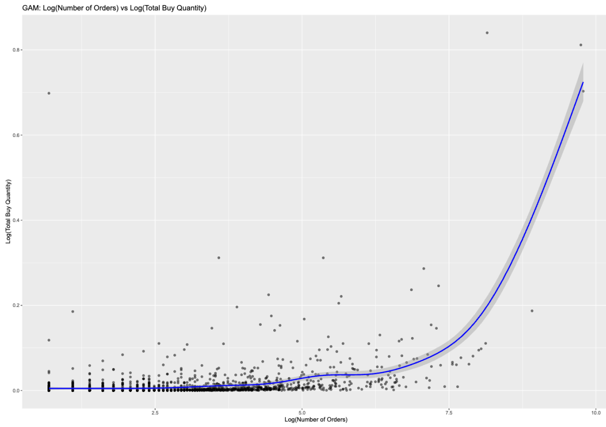

Figure 3: GAM Model: Log(Number of Orders) vs Log(Total Buy Quantity).

To further evaluate the GAM, I examined its summary statistics seen here:

```
> gam_summary

Family: gaussian
Link function: identity

Formula:
log_total_buy_quantity ~ s(log_n_orders)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0128991  0.0008159   15.81   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                 edf Ref.df     F p-value
s(log_n_orders) 8.61   8.94 155.8  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.447   Deviance explained = 44.9%
GCV = 0.0011547  Scale est. = 0.0011483  n = 1725
```

Figure 4: GAM Model: Diagnostic Plots.

The parametric coefficients validated the baseline value of the log total buy quantity when the log number of orders is zero. The small standard error and significant p-value indicated that the intercept was reliable.

The smooth term for the log number of orders had an estimated degrees of freedom of 8.61. This confirmed a non-linear relationship, as a strictly linear relationship would have resulted in an estimated degrees of freedom of one. The value of 8.61, just below the upper bound of 8.94, suggests the model captures the variations in the data without overfitting. The F-value for the smooth term was 155.8, indicating that the smooth term explained a significant portion of the variability in the response variable. The associated p-value further confirmed the statistical significance of the smooth term.

For model fit, I looked at the adjusted R-squared value and the generalized cross-validation score. The adjusted R-squared value was 0.447, meaning that 44.7 percent of the variability in the response variable was explained by the model. While this value is not extremely high, it is still a reasonable result given the noise in the data. The generalized cross-validation score was 0.0011547, which is low and indicates that the model has good predictive power.

To better understand the quality of the model, I generated diagnostic plots, including the QQ plot of residuals, residuals versus the linear predictor, a histogram of residuals, and residuals versus fitted values.

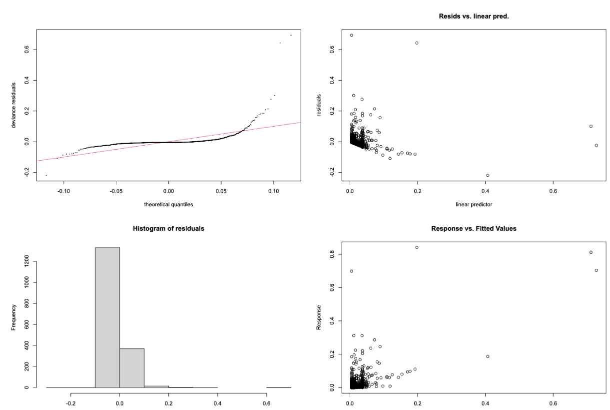

Figure 5: GAM Model: Diagnostic Plots.

The QQ plot showed that the residuals deviate from normality, particularly in the tails, which exhibit skewness. This suggests that the model struggles to capture the variability in certain regions of the data. The residuals versus linear predictor plot displayed a slight funnel shape where residuals fan out as the fitted values increase, indicating heteroscedasticity, or non-constant variance.

The histogram of residuals revealed a skew toward zero, with a high concentration of small residuals and some outliers, which further suggested non-normality. Finally, the response versus fitted values plot showed that many points were clustered at lower fitted values, with increasing deviations for higher values. This indicates that the model has difficulty making accurate predictions for extreme or higher values in the dataset.

While these diagnostics highlight certain limitations of the GAM model, such as non-normality of residuals and heteroscedasticity, the model still performed better than the linear models. Additionally, understanding where the model struggles provides valuable insights for future improvements. Outliers in the dataset likely have a disproportionate effect on the model, and addressing them could improve the fit. Another potential improvement would be to use a different family, such as Gamma or Quasi, to better handle the heteroscedasticity.

To quantify the uncertainty in the GAM model's predictions, I performed bootstrapping. Bootstrapping involves repeatedly resampling the data with replacement, refitting the model for each resample, and aggregating the predictions to calculate confidence intervals. This approach provides a robust measure of uncertainty, particularly in regions where the data is sparse.

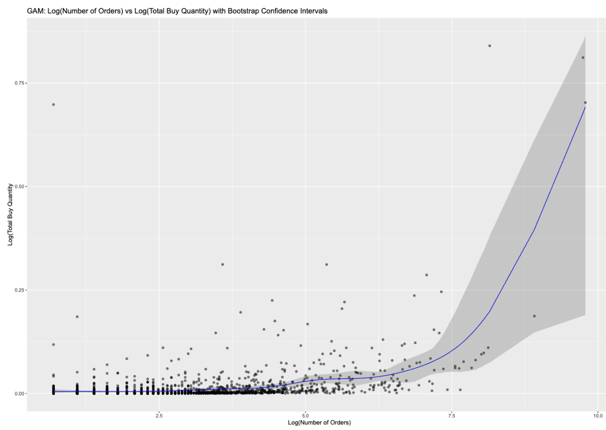

Figure 6: GAM Model: Log(Number of Orders) vs Log(Total Buy Quantity) with Bootstrapped Confidence Intervals.

The bootstrapped confidence intervals are narrow in regions where the data is denser, which indicates that the model's predictions are reliable in these areas. However, as the fitted values increase, the confidence intervals widen, reflecting higher uncertainty in these regions. This is likely due to the presence of outliers and fewer data points at the extremes. Despite this, the majority of the data falls within the range where predictions are reliable. The widening intervals at the extremes highlight where we need to exercise caution with the predictions and provide an opportunity for further refinement of the model.

In conclusion, the GAM model successfully captured the non-linear relationship between the number of orders and total buy quantity, performing better than the linear alternatives. While there are areas where the model could be improved, such as addressing outliers and heteroscedasticity, it remains a reasonable approach for this dataset. Bootstrapping further validated the model by quantifying uncertainty, helping to identify where the model performs well and where caution is needed.

5 Discussion

The results of our analysis provide important insights into user purchasing behavior for the Gods Unchained Cards collection on Immutable X. By exploring the relationship between the number of orders and the total quantity of assets purchased, we gain a clearer understanding of user engagement and economic activity within the marketplace. Our analysis identified a non-linear relationship between the log-transformed number of orders and the log-transformed total buy quantity. The key takeaway here is that users who place a higher number of orders tend to purchase disproportionately larger quantities of assets. This suggests that the marketplace has a subset of highly engaged "power users" who account for a significant portion of the economic activity. These users accumulate more cards and, as a result, exert a greater influence on the secondary market. For Immutable X, identifying these high-order users could allow for targeted strategies or incentives to encourage continued engagement and trading.

While the GAM model effectively captured this non-linear relationship, the diagnostic plots highlighted areas where the model struggles. Specifically, we observed the presence of outliers, non-normal residuals, and heteroscedasticity. The outliers—extreme cases where users have exceptionally high orders or total quantities—may distort the model's performance. These outliers could represent whale users who make significant purchases, speculative trading activity, or bot activity that may disproportionately affect the market. Additionally, heteroscedasticity in the residuals indicates that the model's performance varies across the range of fitted values. This means that the predictions are less reliable for users with very high activity levels, where variability in the data increases significantly.

Despite these limitations, the bootstrapped confidence intervals provide further context to our model's reliability. In regions where the data is denser, such as for users with low to moderate order volumes, the confidence bands are narrow, suggesting that predictions are reliable. However, as the number of orders increases, the confidence intervals widen significantly, reflecting greater uncertainty. This aligns with our earlier findings and reinforces the need for caution when interpreting predictions for extreme-order users. These users represent both an opportunity and a challenge for the marketplace. On one hand, their activity contributes significantly to overall revenue and liquidity. On the other, their behavior may introduce volatility or manipulation that could destabilize the marketplace.

From a broader perspective, these insights suggest several areas for improvement and strategic direction. Understanding the behavior of power users and segmenting engagement based on order activity can help Immutable X design incentives to retain these critical contributors. At the same time, addressing outliers through further analysis—whether to confirm organic behavior or mitigate speculative trading—could improve market stability. There is also an opportunity to refine policies that promote balanced participation in the marketplace, such as encouraging diversity in trading activity or limiting excessive speculation in low-value assets.

The limitations observed in the GAM model also suggest areas for future analysis. Exploring alternative statistical models, such as Gamma family models or quantile regression, may help address the heteroscedasticity and non-normal residuals observed here. Additionally, a deeper understanding of the outliers—whether through data exploration or exclusion—could help improve the overall fit of the model.

In summary, the GAM model provides a

more flexible and accurate representation of the relationship between user orders and total asset purchases compared to linear models. While the model has its challenges, it captures the main trends in the data and provides actionable insights for Immutable X and Gods Unchained. By leveraging these findings, the marketplace can better understand user behavior, target key contributors, and design strategies to foster a healthier and more sustainable ecosystem. These insights also lay the foundation for future improvements, ensuring that the Gods Unchained marketplace remains a vibrant and engaging space for both collectors and traders.