STA302: Factors Contributing to Rocket Launch Success

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Section: LEC0501

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Contributions:

Moeez:

- Team organization and leadership
- Modifying the model
- Completing the final report
- Completing the poster

Lu-Wai:

- Seeking additional variables that could benefit our data
- Modifying the model
- Summarizing our results

Hridansh:

- Completing the final report
- Completing the poster
- Completing the editing techniques

Introduction:

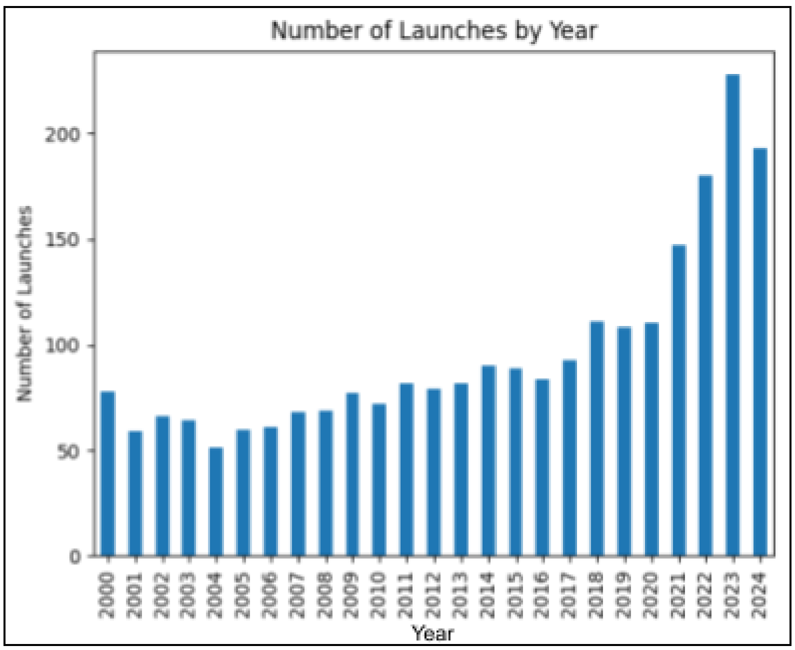

Figure 1: Histogram of Rocket Launches Per Year

It is fascinating to witness a man-made object leaving the place we know as home. With the rapid growth in orbital launches each year (*Figure 1)*, a critical question remains: **How can we ensure their success?** To address this we analyze the impact of factors like vehicle class, cost and day-of-launch conditions on launch success. To this effect, our research question is:
How do factors such as vehicle class, cost, launch site characteristics, and day-of-launch conditions influence the success of rocket launches?

Previous studies primarily focus on launch vehicles as a measure of success. Heuston et al. (1968) analyzed cost dynamics, showing heavily funded and properly maintained vehicles had higher launch success rates. Daniels (2014) supports this by highlighting the importance of technological advancements in vehicle design. Kingwell et al. (1991) examined sudden-onset extreme weather (e.g., high winds and temperature fluctuations) at the Tanegashima Launch Base, Japan, finding these significantly increased failure risk. However, findings such as these are often site-specific. Our study aims to analyze a broader dataset and understand the impact of all these factors together on launch success.

A focus on general launch factors allows us to examine variables like vehicle class, cost, site characteristics, and weather conditions. Linear regression is suitable for this analysis because it'll help quantify the average impact of predictors on launch success and identify the most influential factors. This framework provides a predictive model to forecast future outcomes with a focus on accuracy, ensuring actionable insights for improved launch planning.

Methods:

To provide a visual summary of the steps we carried out, consider *Figure 2* below:

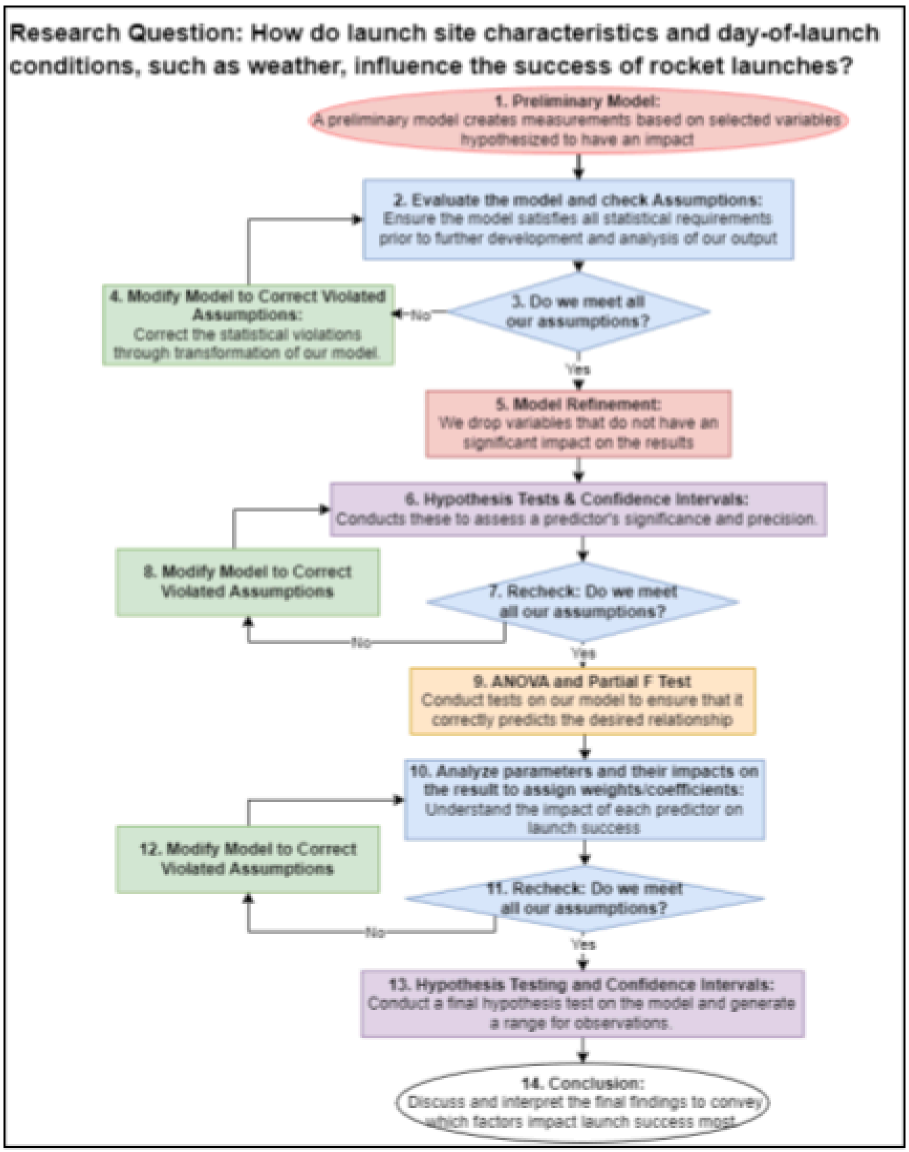

Figure 2: Flowchart Representation of Our Methodology

We started by creating a baseline model, including all predictors to explore the relation between our predictors and the outcome variable (Launch Success). This was a good place to start as it helped us get an initial evaluation of our model. We encoded the categorical predictors in our model before including them in our regression.

The first step in reaching our final model from the baseline model was checking whether the **linear regression assumptions** were met. The check of normality was done using residuals from Q-Q plot, evaluating for any deviations from the line which would suggest non-normality. Independence was tested by making a residuals vs fitted values plot. We looked for any visible clusters or correlations in the residuals as a potential flag for violation. Similarly, linearity was also tested using the same plot by checking for patterns i.e., examining the plot for scatter of values in a non-random pattern. Finally, homoscedasticity was tested by checking if there's an unequal spread of residuals for different fitted values.

The next step was modifying our model to **address the violated assumptions**. Multiple models, each using different transformations were attempted aiming to fix these violations. At every step, our assumptions were rechecked to ensure we are reaching our goal. Log transformations were applied first as they'd address homoscedasticity and normality violations by stabilizing the variance and normalizing the data. Next if that did not work, box-cox transformations were applied to further adjust the skew in the data.

Once all linear regression assumptions were satisfied, we conducted **ANOVA tests**, followed by **partial F-tests**. Both of these helped determine if all our predictors are significant or not. Any predictors with p-value > 0.05 in F tests were dropped.

Another check of the **linear regression assumptions** was conducted at this stage to verify that the new model satisfied them. This check was done in a similar process to the first round of checks. Any violated assumptions were then accordingly addressed similarly to the fixes made to the baseline model.

Next, a **p-value test** was conducted on our refined model to test if it's a significant model. Confidence intervals and hypothesis tests were also conducted on these new models to test the significance of the remaining predictors and assess the presence of a statistically significant relationship.

Finally, once we had a refined model with relevant predictors that are also statistically significant, we **analyzed the parameters** and their impact on the result to assign coefficients to the predictors. This helped understand each individual predictor's impact on our launch success outcome. One final round of linear regression assumption checks and fixes was conducted in a similar manner to the first two checks. Once these checks passed, we had the final coefficients from our reduced model that would help us answer the research question. These coefficients would highlight the predictors and their bearing on the success of a rocket launch according to our model.

Results:

Baseline Model:
Model = Success ~ Year + MeanTemp + MaxWindspeed + LaunchSite + Agency + State

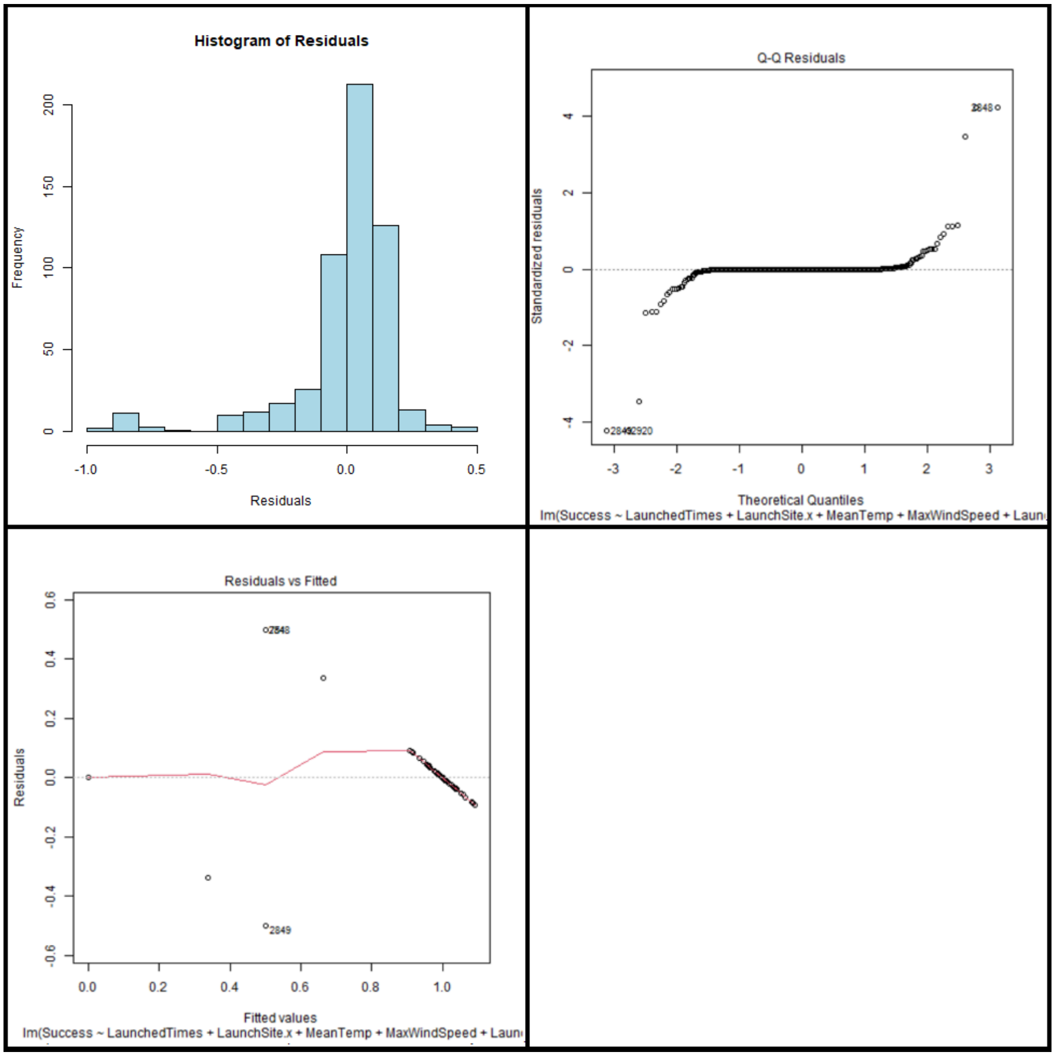

Figure 3: Diagnostic Plots of Baseline Model

Our model from part one took in data of the outcome of a specific rocket launch, with accompanying factors on the day of launch, which was later deemed unsuitable for linear regression. Additionally, we discovered that our data processing from our initial model in part one was flawed, hence producing misleading graphs. While we satisfy our assumption of independence, we incorrectly believed that our model closely satisfied our assumptions of linearity, normality, and homoscedasticity based on *Figure 3* above. As we progressed through our methodology, we discovered that most predictors fail the p-test, and graphs produced indicated assumptions were not valid *(Appendix: Figure 5)*. First, normality was violated due to the heavy-tail distribution of data points, with larger deviation below -1 theoretical quantity. Furthermore, homoscedasticity and linearity were violated as we observed a patterned non-linear spread of residuals.

Intermediate Model:

Model = SuccessRate ~ Year + Price + MeanTemp + RocketYear + Class + State + LaunchSite + LaunchedHistory + LaunchTimes

To address these issues, we overhauled our dataset, as well as the way we processed our data. We found a new data source containing variables such as the cost per kilogram for different launch vehicles, the year that rocket was first launched, as well as the class of rocket (small, medium, or heavy). Our revised dataset included data on the success rate of launch vehicles over the course of a year, with data on launch costs, the class of rocket, average mean temperature experienced by the launch vehicle over the year, average maximum wind speed, average humidity, and more. The improvements made at this stage were significant, and can be viewed below *(Appendix: Figure 5-6)*.

2nd to Final Model (box cox transformed, Lambda Value: 0.9898):

Model = SuccessRateTransformed ~ Year + Price + MeanTemp + RocketYear + Class + LaunchSite + LaunchedHistory

Our intermediate model used our improved dataset, yet similarly still suffered some significant setbacks. After conducting a box-cox transformation, we discovered miniscule improvements on our model, explained by a lambda value close to 1. We experimented with more extreme lambda values such as 0.25, which improved normality, yet did not satisfy our assumptions. While we cannot judge the p-values of our model predictors due to the violation of assumptions, we observed that many failed the test nevertheless. This extended to our ANOVA and Partial F-Tests failing as well. Unfortunately, our attempts to combat these issues, experimenting with interaction terms and further transformations, did not result in a significant improvement.

Final Model:

Model = SuccessRate ~ Year + Price + MeanTemp + LaunchVehicle:LaunchSiteInteraction + Class + LaunchSite

Our final model included all our previous work in order to construct the best model we could, including efforts to filter data, different transformations, and adding interaction terms between our variables. The resulting diagnostic plots and table are as follows: *(Figure 4 and Table 1)*

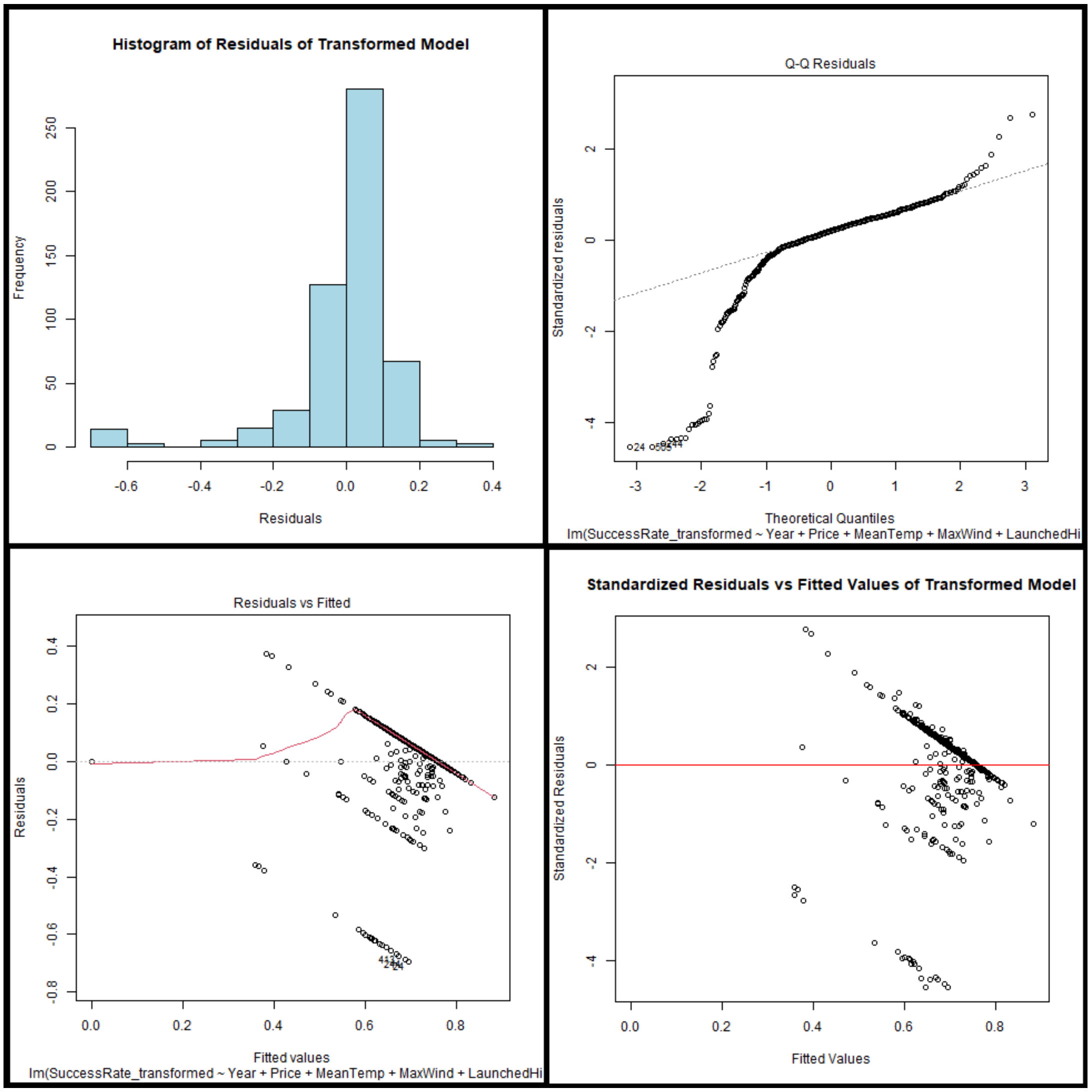

Figure 4: Diagnostic Plots of Final Transformed Model

Coefficients	Estimate	P-Value
Year	5.570e-03	0.00858
Price	3.235e-06	0.00365
MeanTemp	1.962e-03	0.16821
MaxWind	-6.894e-04	0.67393
ClassMedium	4.608e-02	0.21288
ClassSmall	-3.451e-02	0.43776
LaunchSite: Satish Dhawan Center, India	-2.646e-01	0.01727
LaunchSite: Kagoshima Launch Center, Japan	-4.979e-01	0.00195

Table 1: Summary of Model Predictors

The diagnostic plots still display a violation of assumptions as mentioned before, but greatly reduced (compared to *Appendix: Figure 5*). Given the limited timeframe, we decided to formulate our results from this model. It appears that the **launch year** and **price per kilogram** of the rocket both have a positive impact on the success rate of a launch. These results are not particularly surprising, as intuitively:

1) The year of the launch is linked to the natural progression in technology, increasing precision, safety, and reliability of rockets.
2) The price of a launch vehicle suggests greater importance, hence increased necessity for reliability, specifically for missions regarding national defence (US National Security Space Launch Program Requirements).

Our results also indicate that weather conditions, such as the mean temperature and wind speed have an effect on the success rate of a launch. While it has a high p-value, the model indicates that wind speed has an adverse effect on launches. Stronger winds add uncertainty which engineers must account for. On the contrary, the model also indicates that higher mean temperatures have a positive impact on the success rate. Parallels from our weather data can be drawn to the Space Shuttle Challenger disaster in January 1986, caused by an O-ring seal failure due to cold weather and wind shear.

Other predictors, such as the impact of categorical size classifications of the rocket are interesting to note. The results of our model indicate that medium-class rockets have higher success rates, compared to small-class rockets. This may be explained by small-class rockets being developed by less experienced agencies. While launch sites typically had minimal impact on the model, the most impactful ones included India's Satish Dhawan Center and Japan's Kagoshima Launch Center, both with negative correlation to launch success. It is important to note that both India and Japan are relatively inexperienced in developing orbital class rockets compared to nations like the United States, which may explain these results.

Conclusion and Limitations:

We are inclined to believe that, answering our research question, that the factors explored have a bearing on the success of rockets. However, this response to the initial research question could be more confidently stated if our model better satisfied the modeling assumptions. Presently, our verdict is limited by the fact that our assumptions were not satisfied. Referring to *Figure 4* in our results, we were unable to correct all our assumptions:

1) normality is violated by the heavy-tail distribution of data points

2) homoscedasticity and linearity is violated by a non-linear spread of residuals, creating a strong pattern.

We have attempted to correct these assumptions through a variety of models, some of which are above and the rest may be found in the appendix *(Figures 5-8)*. Given further time to analyze our data, we may be able to broaden the number of predictors in our dataset and further research ways to correct our approach to our data. Some techniques used to attempt to mitigate the issues with our model include, but were not limited to; Changing variables, Adding transformations on variables, using Box Cox transformations, adding interactions, filtering out big outliers in the dataset, overhauling our dataset, and much more. Given the issues with our initial values, we put in substantial time and effort, in order to try a variety of methods in order to improve our model.

It is possible that our dataset was not complete and limited by the parameters available. More detailed information and engineering considerations could not be included in our research as these were not compiled in a dataset/API or they were confidential to be cleared for public access. Comprehensive open datasets on rockets, and rocket launches across the globe can be hard to come by, since access to space is often considered a matter of national security, and details of launch vehicles are closely guarded secrets. While it might be beneficial to implement such information in our model, it was not an option for us. In further studies, researchers may invest their initial efforts into compiling such pre-requisite data, creating a dataset that all statisticians could refer to going forward.

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Appendix:

Initial plots generated, before final attempt to mitigate model issues

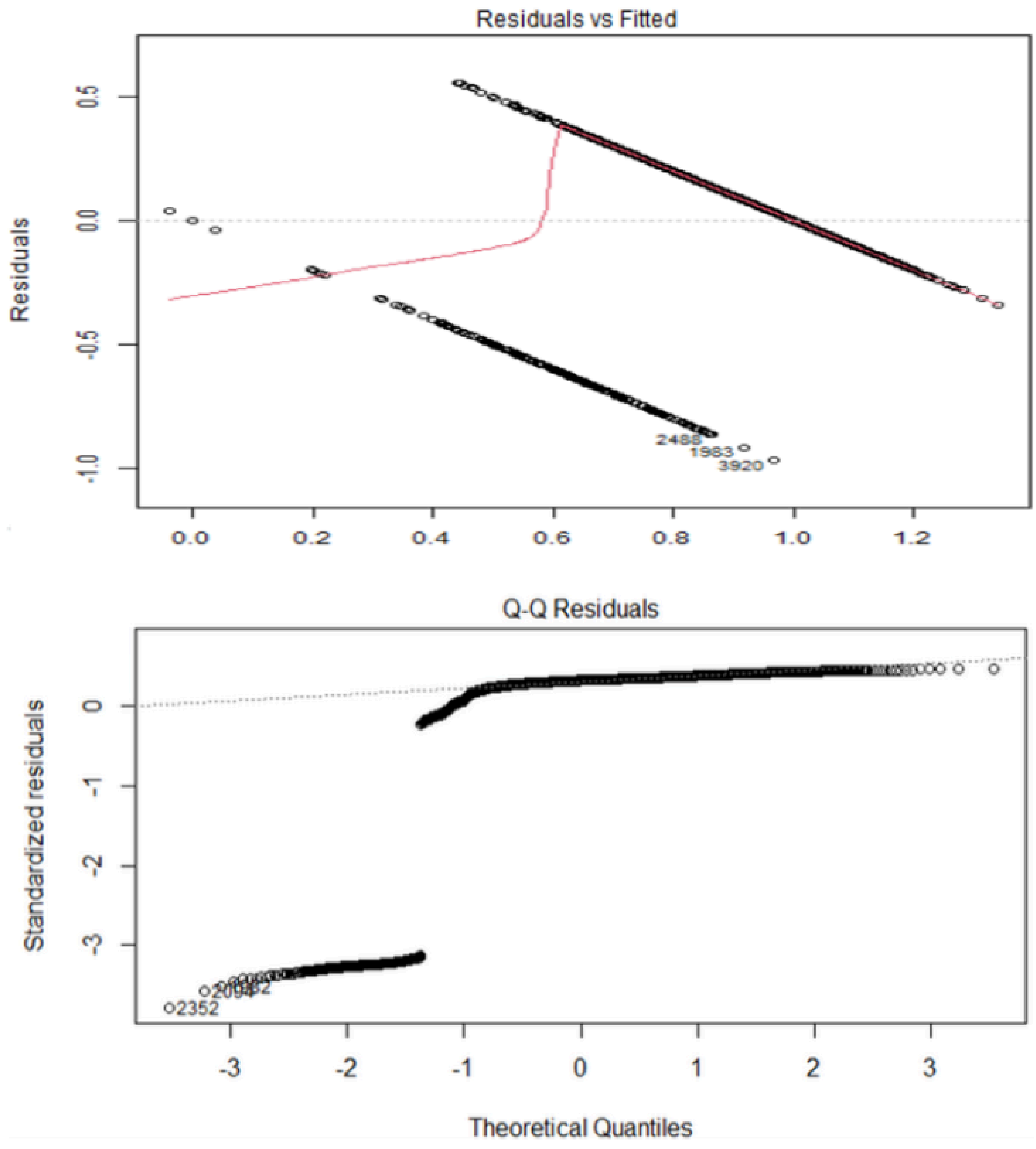

Figure 5: Diagnostic Plots of Corrected Baseline Model After Cleaning Data

In Between Plots After Changing Data Format/Source

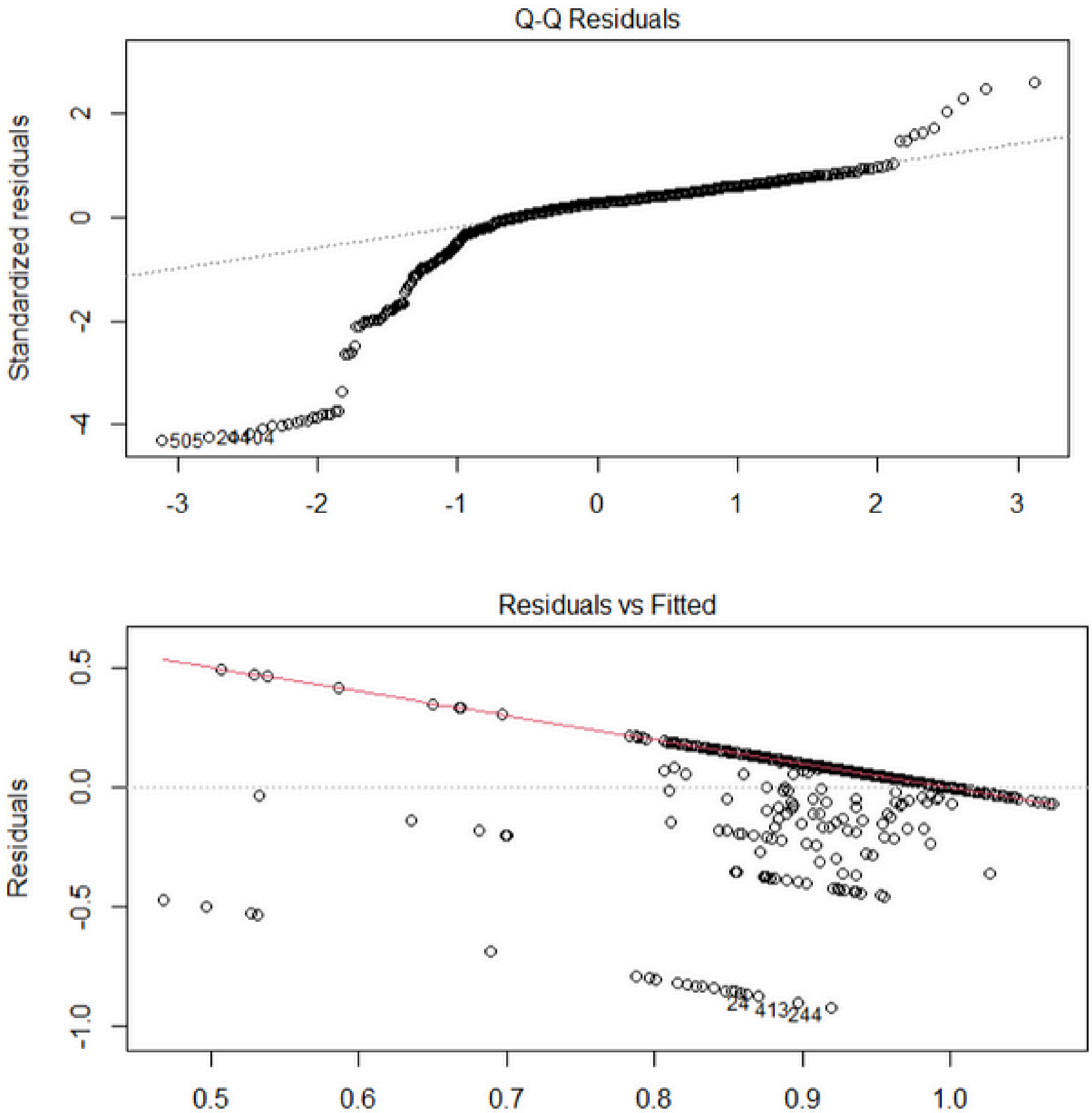

Figure 6: Diagnostic Plots Of In Between Data, With Updated Data Formatting