Analysis of Vance County EMS Ambulance Distribution

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1 Background

The Vance County Emergency Medical Services system currently operates four ambulances and two stations with one located in the Southern district and one in the Central district. This configuration leads to the underserving of residents in the Northern district, with higher average response times than the other two districts. Such delays can lead to critical differences in patient outcomes especially in life threatening emergencies.

In response to this issue and demand for EMS coverage in the North region, Vance county is evaluating the option of adding a new station in one of the two northern locations: near north or far north station. We use historical EMS call data to make a decision. Each record in the dataset represents one individual emergency trip which includes information like dispatch station, patient location coordinates, and time logs for dispatch, arrival, hospital transport, and clearance.

The main motivation of this analysis is to assess how travel times and system load vary across different station allocation scenarios, listed in Table 1 (appendix). In particular, we aim to answer the following central questions: 1) which of the two possible Northern station locations (Near vs Far) would better serve the community through faster response time 2) which station's relocation to the North (South vs Central) would yield to improved response time and 3) which combination of allocation of the four available ambulances across stations would best optimize service coverage and response times.

2 Exploratory Data Analysis

To understand the distribution of our data, we first model the best-guess travel time for all data points into a histogram (Figure 1) and observe that the South station has shortest median travel time. Both the Near North and Far North stations, on the other hand, have longer travel time with wider variability as expected. We can observe that the Far North station has the widest spread and most outliers, implying more inconsistent travel times possibly stemming from its remote location and small sample size.

We then examine the occurrence of "load conflicts" in each region, defined as stress events wherein overlapping calls occur when ambulances are already occupied. Comparing the distribution of load conflicts in Central and North regions (Figure 3) versus the South (Figure 4), we find significantly more load conflicts in the Central and North regions in the baseline scenario. We also observe that most conflicts are short, lasting a few minutes and occurring on a nearly daily basis. However, observng the heavy tail in Figure 3, it can be seen that some extreme cases develop into "critical stress events" which we define as 3+ load conflicts occurring at once. This suggests that response times could be delayed disproportionately for North stations.

3 Model Assumptions & Assessment

As a foundational assumption to follow for all scenarios, we set a "dispatch rule" on how ambulances will be dispatched depending on location of the call. For scenario 0 (current baseline) where 3 ambulances are in Central and 1 is in South station, we assume that all North and Central calls are taken by the Central station and all South calls are taken by the South station ambulances. For scenarios 1 and 2, still with 3 ambulances in the Central station but with 1 South ambulance relocated to the North (Near or Far, respectively), we assume that North calls are taken only by the North station and Central or South calls are only taken by the Central station ambulances. For scenarios 3 and 4, with 1 South ambulance, 2 Central ambulances, and 1 Central moved to the North (Near or Far, respectively), we assume all calls are taken by an ambulance from its same-region station. However, we make an exception to these rules in the case of critical stress events at an assigned station, as it would be unethical to "gatekeep" ambulances from dispatching to a different region when they are available. In such cases of 3+ load conflicts, we make the available ambulance from the next closest station to be dispatched to take the call.

Under the assumption of a hierarchical approach where we condition on the calls over the total change in time, we fit a couple of models. The covariates are __________. They are both linear mixed models where utilize a random effect for a call since there is within group variation for each call. One takes into account heteroscedasticity concern and varies potential errors by longitude and latitude. To access these model assumptions we examined the residual plots for both candidate mixed models. **Figure 6** shows the model with constant error variance has residuals that are centered around 0 with no strong curvature so the assumption of linearity is reasonable here even though there are some spread, the pattern is not indicative of systematic heteroscedasticity. **Figure 8** is the one where we allowed the error variance to differ by scenario and it shows no meaningful improvement in the residual spread or overall structure. Since the more complex variance structure did not really reduce the heteroscedastic pattern, the simpler model without additional error variation is preferred.

4 Results

We note that there are different residuals for the aforementioned fits. We find that when examining the normality condition, that the model without the error variations seems to be a better fit for the data as seen in **Figures 7 and 9**, and consequently we analyze the results under the fit without the additional variation.

Our final model is the following linear mixed model:

$$Response\ Time \sim Scenario + Distance + RushHour + (1|CallID) + \epsilon$$

For fixed effects, we included scenarios as a categorical variable, with S0 as baseline and S1~S4 as changes. Distance from the station to the call location was set as a continuous variable. We also decided to include rush hour as binary variable to account for traffic level, by categorizing the time of day into non-rush vs rush hour. We defined rush hour to be 7:30-9:30AM and 4:00-6:30PM for each day, as per observation of average traffic levels. The model's random effects accounted for variation by call group, and residual error modeled day-to-day variance.

For model assumptions, we first let residual error follow a normal distribution, We also assumed traffic level to be consistent within and outside rush hours, to simplify traffic levels on a binary level rather than continuous. Based on our residual plot, we did not model for heteroscedasticity for random effects as it led to a better model fit. Finally, we assumed that if distance is the same, the actual latitude and longitude coordinates would not affect response time differently.

Table 2 is our coefficient summary for the better fit model. We can see that the estimated coefficients for all four Scenario indicators have p values that are greater than 0.05 and their 95% confidence intervals all cross zero which indicates that holding Distance and Rush Hour constant, there is no statistically significant evidence that response time differs across the alternative allocation scenarios compared to the baseline configuration of S0.

So from our analysis we have found that 1) there is not statistically significant difference in response time between the near north and far north stations and both scenarios perform similarly once we adjust for distance and rush hour, 2) there is no statistically significant difference in response time when we move the station north from the central or south stations and 3) relocating to north station does not yield any significant benefits as the relocation scenarios as a whole do not yield statistically significant improvement in response time.

5 Conclusion and Future Work

Our analysis showed that relocation to far north resulted in faster response times than near north. We have also shown that it is better to move central ambulances up north than moving the south ambulance and saw that relocating one ambulance from central to far north station reduces response times by about 4%. Therefore from our analysis we saw scenario 4 which is 1 far north, 2 central, and 1 south was the most optimal layout of the 4 ambulances as it reduces the average response time by 4% compared to the baseline of scenario 0.

Some limitations is that our model assumes traffic level to be constant throughout non-vs rush hour. We also are dealing with data that has error introduced by data randomization from the HIPAA protection so there is some marginal error in the distance calculation that stems from this. We are also limited from the smaller sample size and also from the best guess Google API which assumes average conditions.

In the future we can try adding time of day for a random effects which could provide a deeper insight into temporal variation in the response times. We can model this using a continous smooth spline approach using mgcr or poly to capture the nonlinear daily trends without overfitting. We can also try a Bayesian approach to improve interpretability, particularly in regions with fewer calls. Through partial pooling and uncertainty propagation, the use of this approach would allow information sharing across districts while accounting for data sparsity. Finally, a hierarchical modeling approach could be implemented to account for further subdivisions in call type and urgency and this would allow our model to distinguish between the emergency severity levels and incorporate medical criteria for the urgency of each call which could change how we allocate the ambulances across the systems.

6 Appendix

Exploratory Data Analysis

Figure 1

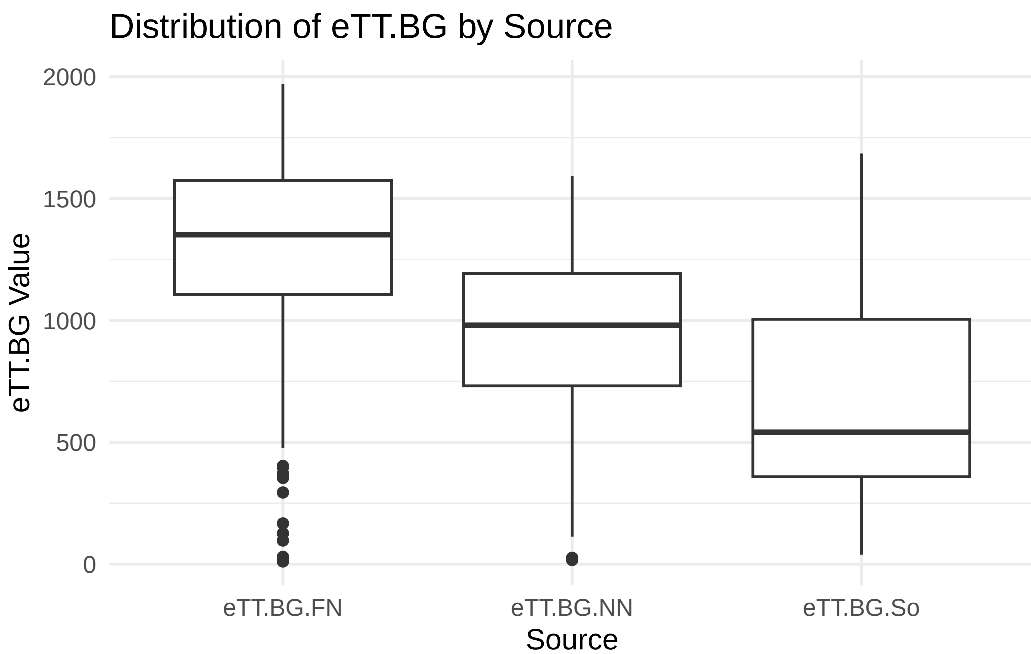


Figure 2

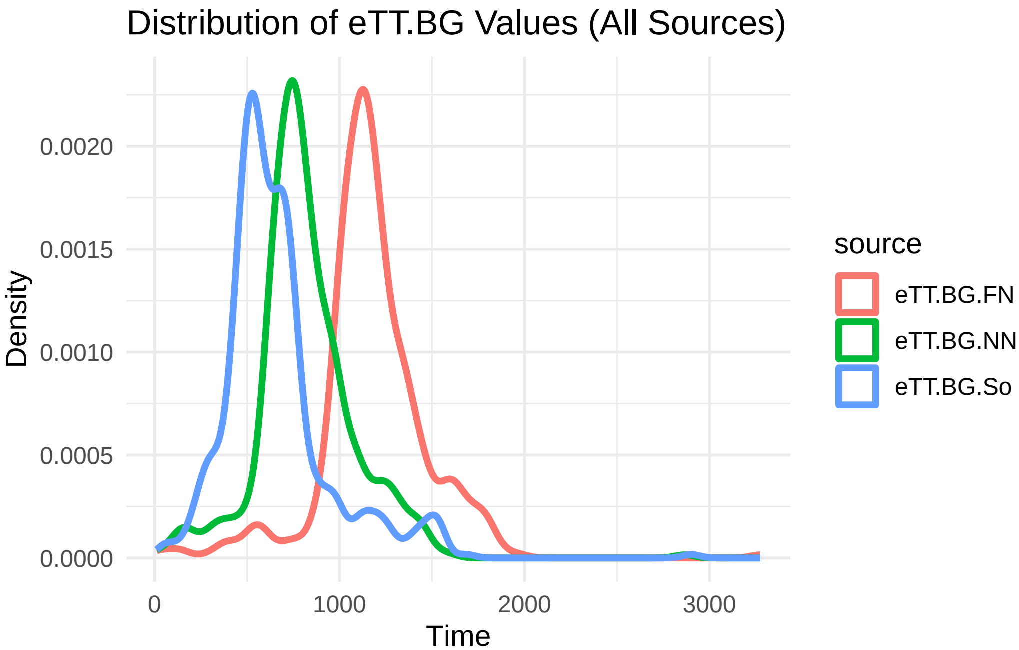

Distribution of eTT.BG Values (All Sources)
Density
0.0020
0.0015
0.0010
0.0005
0.0000
0
1000
2000
3000
Time
source
eTT.BG.FN
eTT.BG.NN
eTT.BG.So

Figure 3

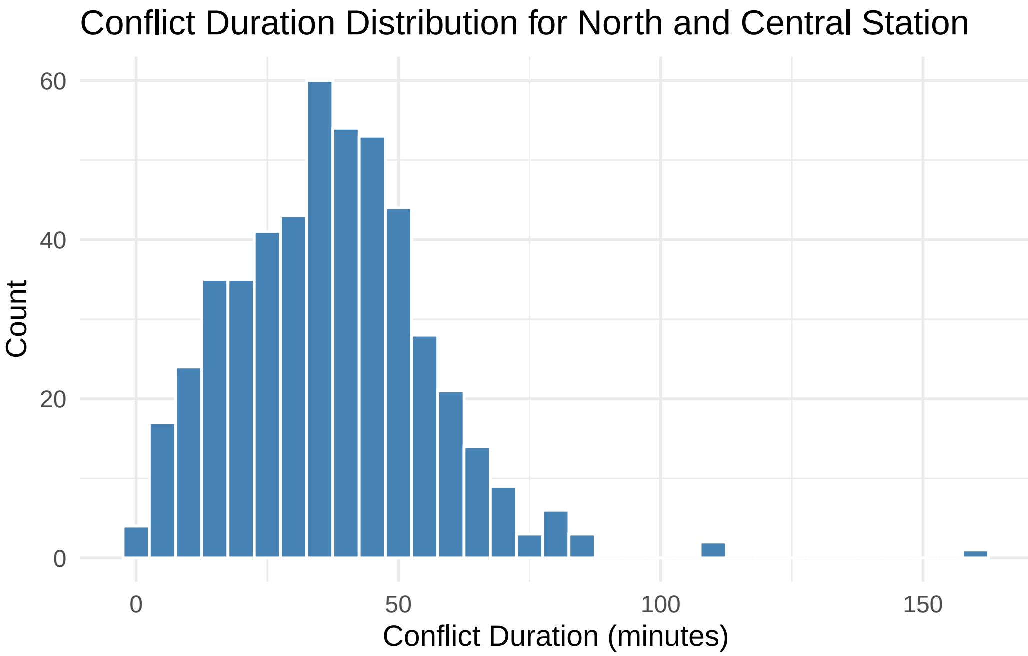

Conflict Duration Distribution for North and Central Station
Count
60
40
20
0
0
50
100
150
Conflict Duration (minutes)

Figure 4

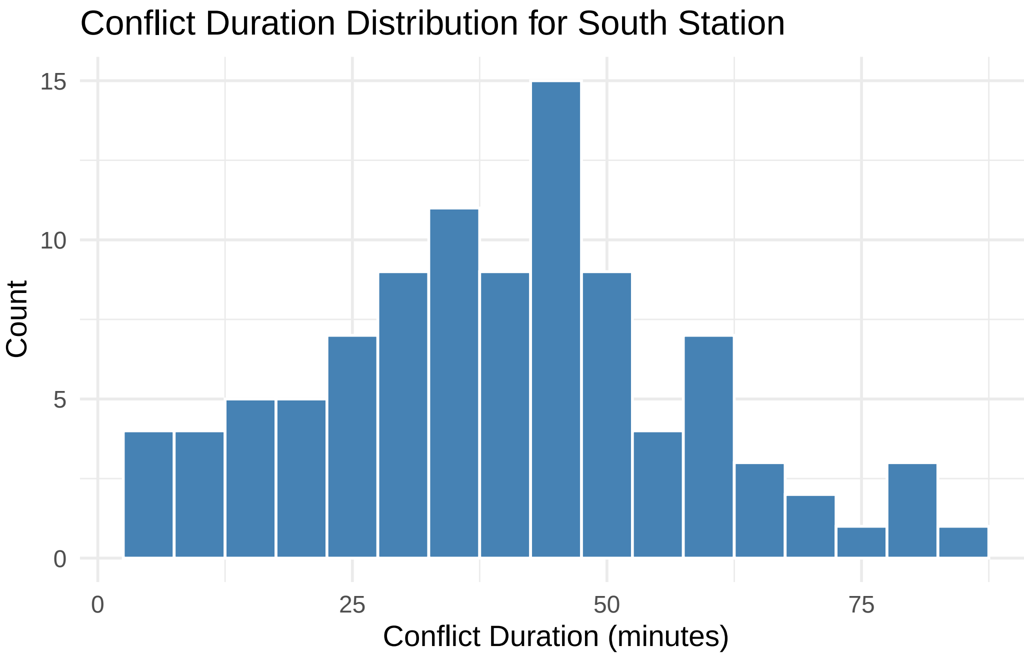
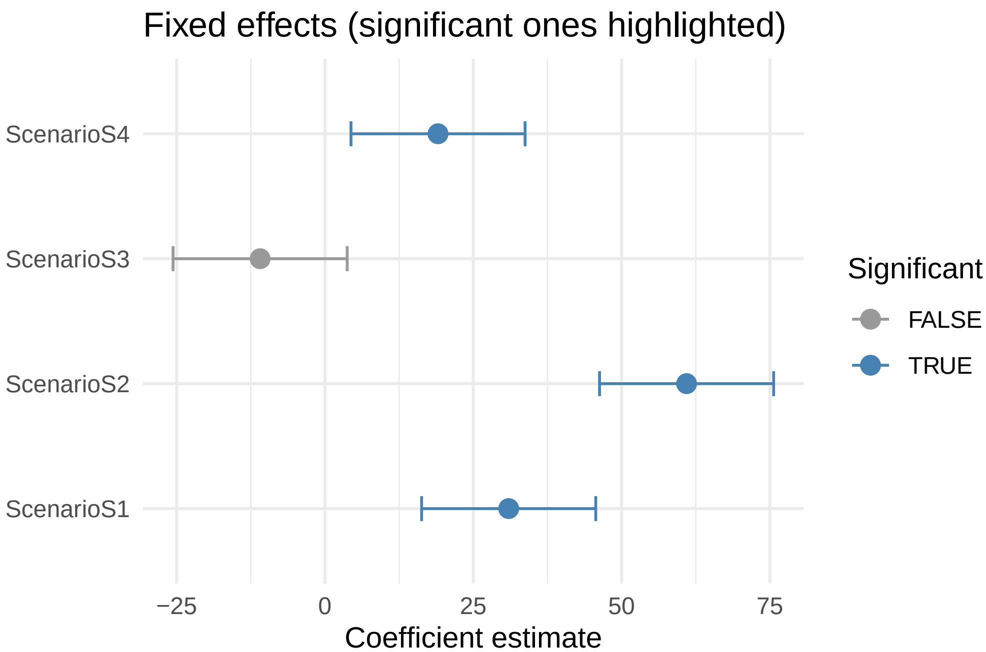

Conflict Duration Distribution for South Station
Count
15
10
5
0
0
25
50
75
Conflict Duration (minutes)

Figure 5



Fixed effects (significant ones highlighted)
ScenarioS4
ScenarioS3
ScenarioS2
ScenarioS1
−25
0
25
50
75
Coefficient estimate
Significant
FALSE
TRUE

Modeling

Table 1

Scenarios	**S0 (Current)**	**S1**	**S2**	**S3**	**S4**
Far North	0	0	1	0	1
Near North	0	1	0	1	0
Central	3	3	3	2	2
South	1	0	0	1	1

Table 2

Linear Mixed Model for EstTravelTime

	EstTravelTime			
Predictors	*Estimates*	*std. Error*	*CI*	*p*
(Intercept)	112.04	8.75	94.85 – 129.22	**<0.001**
Scenario [S1]	-5.35	6.48	-18.07 – 7.36	0.409
Scenario [S2]	-4.99	6.74	-18.22 – 8.24	0.459
Scenario [S3]	-3.37	6.38	-15.90 – 9.17	0.598
Scenario [S4]	-3.01	6.41	-15.60 – 9.59	0.639
Distance	0.05	0.00	0.04 – 0.05	**<0.001**
rush hour ind	11.86	13.32	-14.29 – 38.01	0.373
Random Effects				
σ^2	3068.93			
$\tau_{00\ \mathrm{CallID}}$	4157.26			
ICC	0.58			
N_{CallID}	151			
Observations	755			
Marginal R^2 / Conditional R^2	0.928 / 0.969			

Figure 6

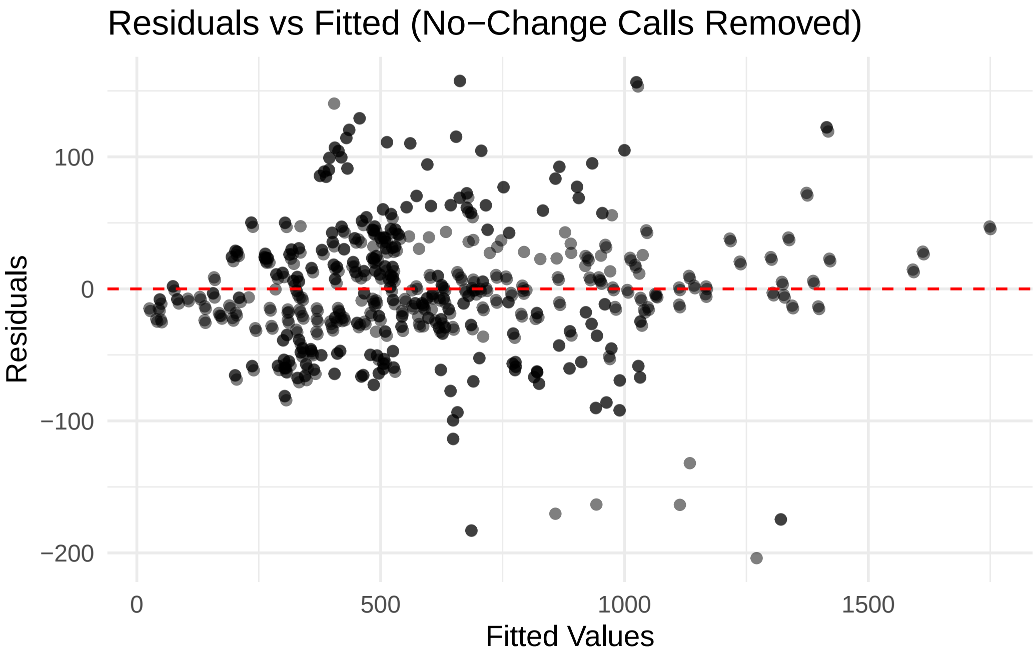

Residuals vs Fitted (No−Change Calls Removed)
Residuals
100
0
−100
−200
0
500
1000
1500
Fitted Values

Figure 7

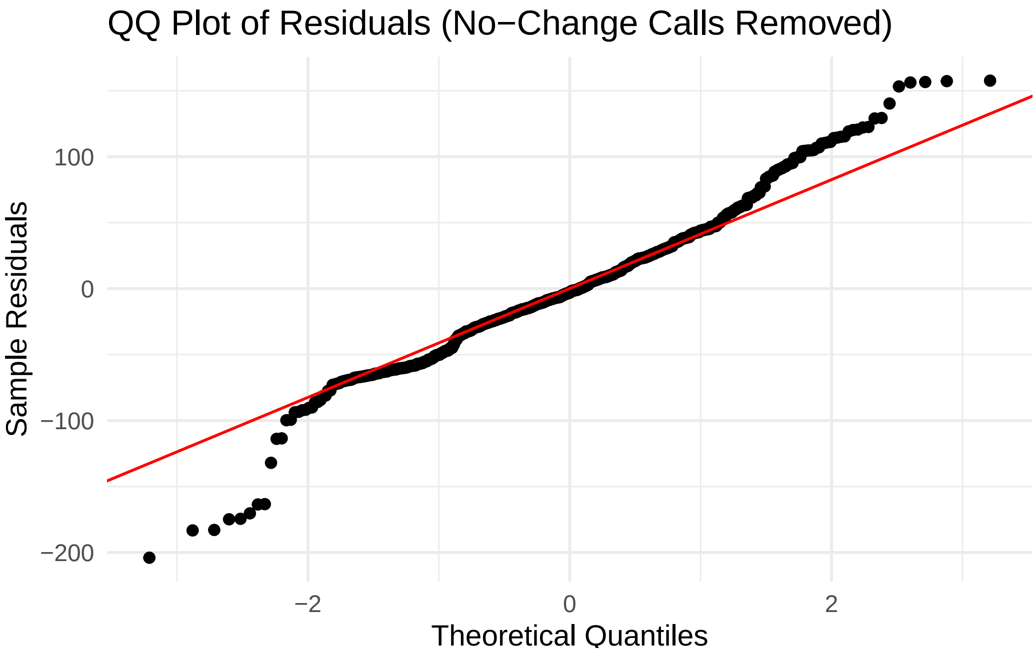

QQ Plot of Residuals (No−Change Calls Removed)
Sample Residuals
100
0
−100
−200
−2
0
2
Theoretical Quantiles

Figure 8

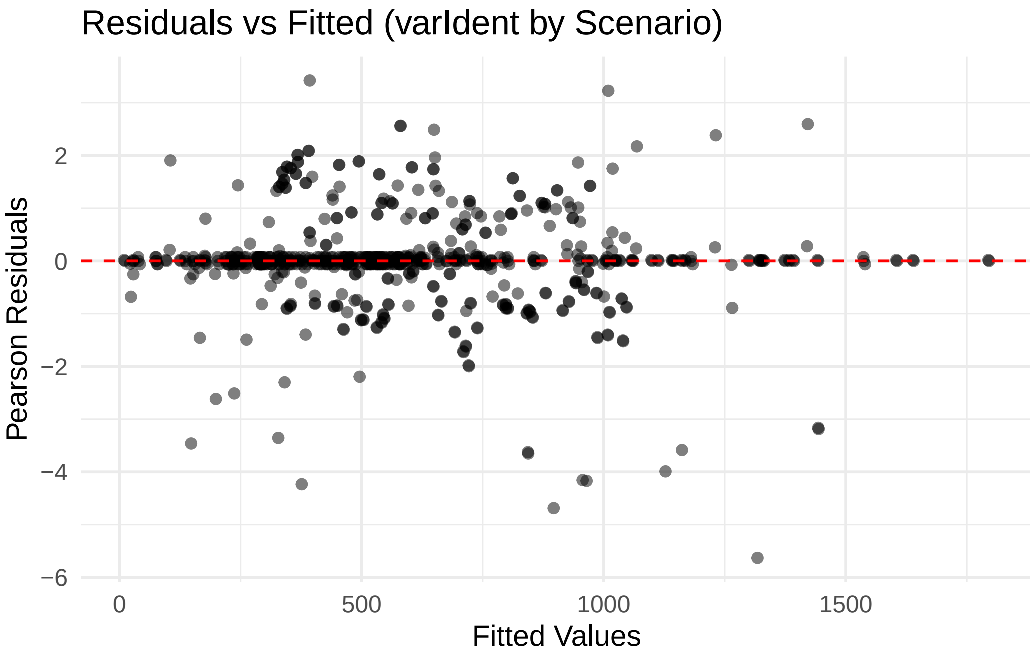

Residuals vs Fitted (varIdent by Scenario)
Pearson Residuals
2
0
−2
−4
−6
0
500
1000
1500
Fitted Values

Figure 9

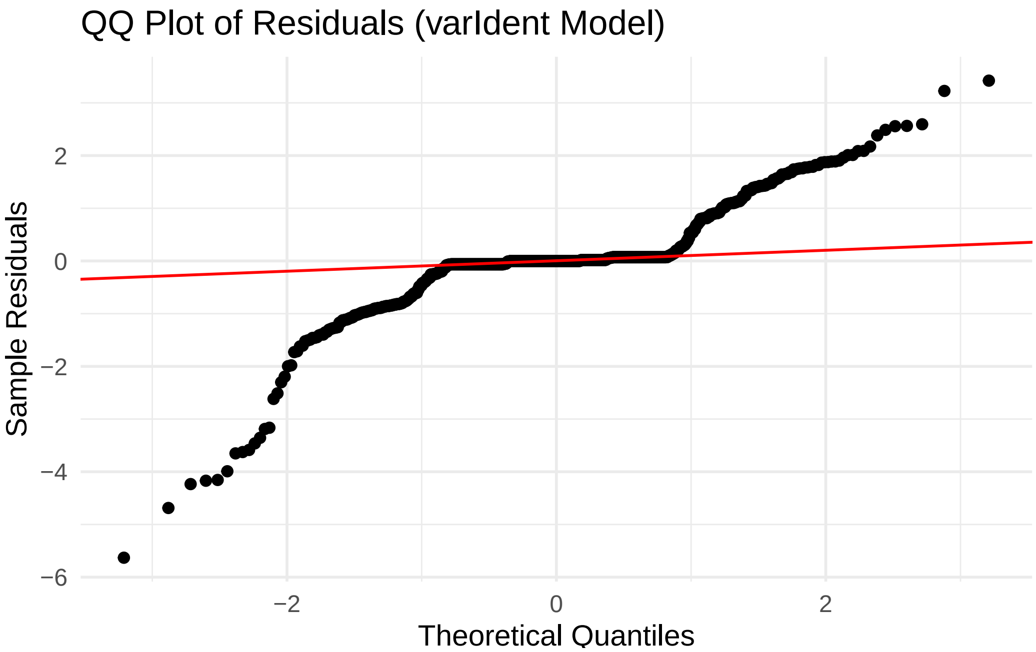
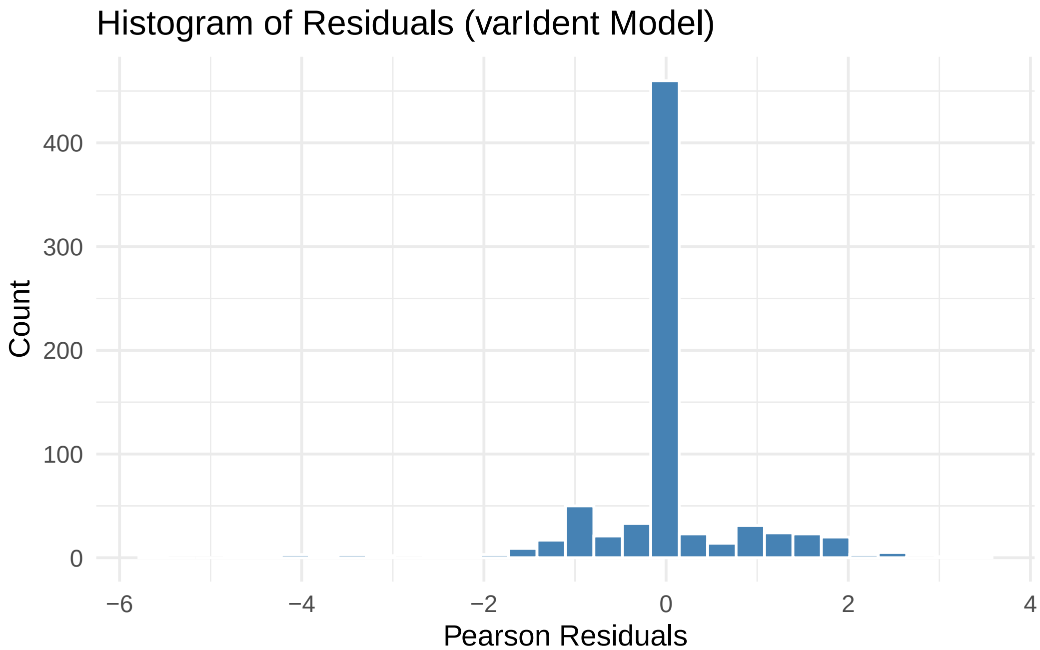

QQ Plot of Residuals (varIdent Model)
Sample Residuals
2
0
−2
−4
−6
−2
0
2
Theoretical Quantiles

Figure 10



Histogram of Residuals (varIdent Model)
Count
400
300
200
100
0
−6
−4
−2
0
2
4
Pearson Residuals