Effects of Work Shift and Total Excercise Time on Weight Gain

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Abstract

Our study examined 230 employees at a call center in the American South and their self-reported weight gain over a period of eight months. Our primary focus was determining how and to what extent Total Metabolic Minutes, an intensity-weighted measure of time spent exercising, and the employee's shift start time had on the amount of weight they gained in that span. Controlling for gender was key, as it had a substantial impact on how the other predictors behaved. Since only weight *gain* was measured, employee weight change became censored at zero, so we used zero-inflated Poisson regression to model the number of pounds gained. Although the binomial portion of the model was unable to find significant predictors for whether or not an employee gained weight, once the employee did gain weight, the Poisson portion of the model performed well modeling and predicting weight gain. Increasing Total Metabolic Minutes exercised and starting work at a later time (working a later shift) were both statistically significant and associated with lowering the expected weight gain for the employee. The decrease in expected weight gain associated with later shifts was even more pronounced for men than for women. However, the net effect of metabolic minutes on weight gain was lower for employees with later shifts, so exercise did less for those who started work later in the day.

1 Introduction

Our task was to determine how time spent exercising (measured in Total Metabolic Minutes) and shift (time of day a person's job begins) impacted the amount of weight gained over an eight month period for employees at a call center in the American South. Out of over 1000 employees, 342 provided us with information on their weight gain, and of those, only 238 provided us with information on all of the predictors we felt were relevant for our study. Eight extreme values for weight gain were identified as outliers, and those cases were removed for the benefit of the study. 230 subjects were then used for the final analysis - 155 who gained weight and 80 who did not. Gender (152 female, 78 male) was used as a predictor in the study, as it had clear impact on the values of our predictors and of our response. Job and Department were excluded as variables, as all of the information contained in both of those variables are posited to be contained in the shift variable. Beginning weight of the participant and their age were also included as predictors since they had an effect on the time a subject spent exercising. Only one transformation of our predictors was used: the log of Total Metabolic Minutes.

Ultimately, we settled on a zero-inflated Poisson model, which uses a logit-link to the binomial for determining if an employee crosses the threshold of gaining weight, and then a log-link to the Poisson for determining the number of pounds gained once the threshold is crossed. Although weight gain is an inherently continuous random variable, we are using two discrete distributions (binomial, Poisson) to model it. This is because whether or not one gained weight is a binomial process, and the vast majority of respondents round their weight or weight change to the nearest whole pound. Thus, modeling the number of pounds gained in a fixed time period as a Poisson random variable of counts does not feel inappropriate in this setting, especially since the shape of the distribution of pounds gained fits so well. The ease of interpretation of the results of the analysis was also considered as a reason for choosing this method.

Our study finds that the number of pounds gained was reliably modeled by a truncated Poisson; however, no variables were able to significantly predict whether or not somebody gained weight (the binomial part of the model). If somebody did gain weight, though, we found that Total Metabolic Minutes, shift, and the interaction between them to be the three most significant predictors. We found that increasing total metabolic minutes did lower the expected number of pounds gained as anticipated, and having a later shift also lowered the expected number of pounds gained; however, the interaction between shift and total metabolic minutes indicated that the net effect of metabolic minutes on weight gain was less pronounced for employees with later shifts. We also find that the benefits of lower average weight gain associated with a later shift is even more pronounced for males than females. In other words, out of all of the employees who do gain weight, weight gain is the least pronounced, on average, for those who exercise more, come into work at a later time, and identify as male.

2 Causal Inference for Model Selection

In order to address the effects of shift time and exercise on weight gain with only observational data, we must first construct a theoretical causal model showing the hypothesized relationships between the two primary predictors, the response, and any potential confounding variables that we have measured.\ What follows is a list of the predictors and potential confounders under consideration with their hypothesized effects on weight gain and on the other predictors:

- **Total Metabolic Minutes:** This variable represents total exercise time for respondents in an average week, weighted by the intensity of the exercise. We expect exercise to have a direct effect on weigh gain, most likely with an inverse relationship.
- **Shift:** This variable indicates the shift in which respondents begin their work day. We expect shift to have an effect on total metabolic minutes, since workers may struggle to fit regular exercise into their daily routines depending on their work schedules. Additionally, we are interested in modeling any potential direct effect of shift on weight gain to see if the call center could implement some change to their schedules to facilitate better health.
- **Age:** We expect the respondent's age to have some effect on total metabolic minutes, since people may find more vigorous exercise more difficult as they age. It may also affect the respondent's beginning weight. Additionally, we expect some direct effect of age on weight gain as metabolism changes with age.
- **Gender:** The respondent's gender likely affects total metabolic minutes as men and women might tend to engage in different types of exercise on average, and we can expect beginning weight to be affected since men are heavier than women on average. It may also have an effect on weight gain, assuming that the is some difference between the metabolic processes of mean and women on average.
- **Beginning Weight:** We can expect some influence of initial weight on total metabolic minutes, since the respondent's weight may inform us to their propensity to exercise. It may also impact weight gain, assuming that it serves as a proxy for overall health or innate metabolic levels. It also may just serve as measure of capacity to gain weight. The larger a person's natural frame, the more weight they can gain and carry at any time.
- **Job and Department:** Employees typically apply for a job without consideration for which department of a corporation intends to hire them, so their job will determine their department. Shifts will be set depending on the nature of the job and on departmental policy. Since these call center jobs are all white-collar and service jobs, there is little reason to expect an effect on weight gain beyond the effect of the jobs on the respondants' work schedules.
- **Walk, Moderate, and Vigorous Exercise Time:** These three variables are added together in a linear combination ($8 \cdot \texttt{Vigoroustime} + 4 \cdot \texttt{Moderatetime} + 3.3 \cdot \texttt{Walktime}$) to calculate total metabolic minutes, so the information contained within them is already included in a model with TMM.

These relationships can be illustrated in a Directed Acyclic Graph (DAG) with arrows indicating the direction of causation between the variables (Textor et al., 2017). When there is a confounding variable influencing both one of the predictors and the response, the effect of that predictor must be conditional upon that confounder (i.e. it must be included in the regression model as an adjustment). When an additional variable only has a pathway through one of the predictors to the response, then its information is already contained within the predictor, and it should be excluded by the model (Greenland et al., 1999). Following these principles, and assuming our causal model is correctly specified, we find that our main-effects model for weight gain on work shift and TMM must also adjust for beginning weight, age, and gender (Figure 1).

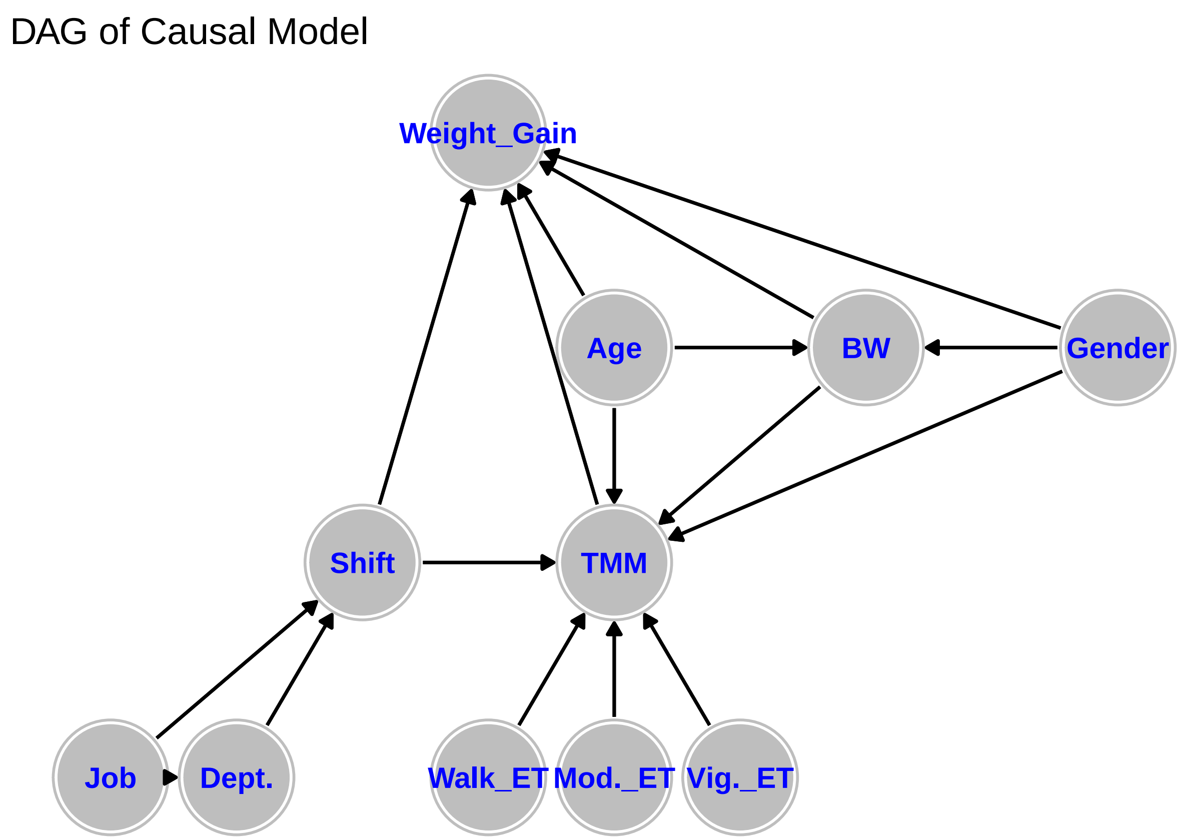

Figure 1: The causal model shown above indicates adjustments for age, beginning weight, and gender will be necessary to correctly estimate the effects of work shift and Total Metabolic Minutes

3 Exploratory Data Analysis and Transformations

With the main-effects model broadly specified, we turn our attention to the question of whether or not our model may benefit from applying transformations to the predictors. In general, we want to ensure that our observations are roughly symmetrically distributed, but also to avoid unnecessary transformations that may hinder easy interpretation of the model's coefficient estimations. Our approach will depend on visual interpretation of histograms.

The distribution of total metabolic minutes (Figure 2) is strongly right-skewed and evinces a clear need for transformation. The range of observations crosses several orders of magnitude, from 0 to well over 10,000, which implies that a natural logarithm would be an appropriate transformation. The log transformation was performed on TMM+1 to avoid cases of log(0) which is undefined. The resulting distribution is far less skewed, but is bi-modal with one peak at 0 and another around 7.5. despite the bi-modality, we will proceed with the log-transformation since it effectively compresses the range of TMM to better match the rest of the variables.

For ease of interpretation, we have chosen to model shift as an ordinal variable, allowing us to analyze the effect of starting work earlier or later. This decision requires the assumption that "other" shifts are later than the given shifts, but this may not be unreasonable since most of the early hours of the day are covered by the given shifts. Most shifts start at 8 am, which skews the distribution somewhat, but the rest of the shifts are rather evenly dispersed, so we shall proceed without any farther transformations (Figure 3).

Females outnumber males in our sample by at least 2 to 1, but the total counts for each are well over 50, giving a sufficient sample size to analyze (Figure 4).

The distribution of ages is fairly right-skewed (Figure 5), but applying a log-transformation does little to reduce the skew. Since the ages do not cross an order of magnitude and the logarithm will not improve the model more than it will hinder direct interpretation, we have elected to use the untransformed ages in our model.

The distribution of beginning weights is somewhat right-skewed (Figure 6), but not improved much by a log-transformation —much like the ages. Again, there does not seem to be sufficient cause for transforming beginning weights in our model.

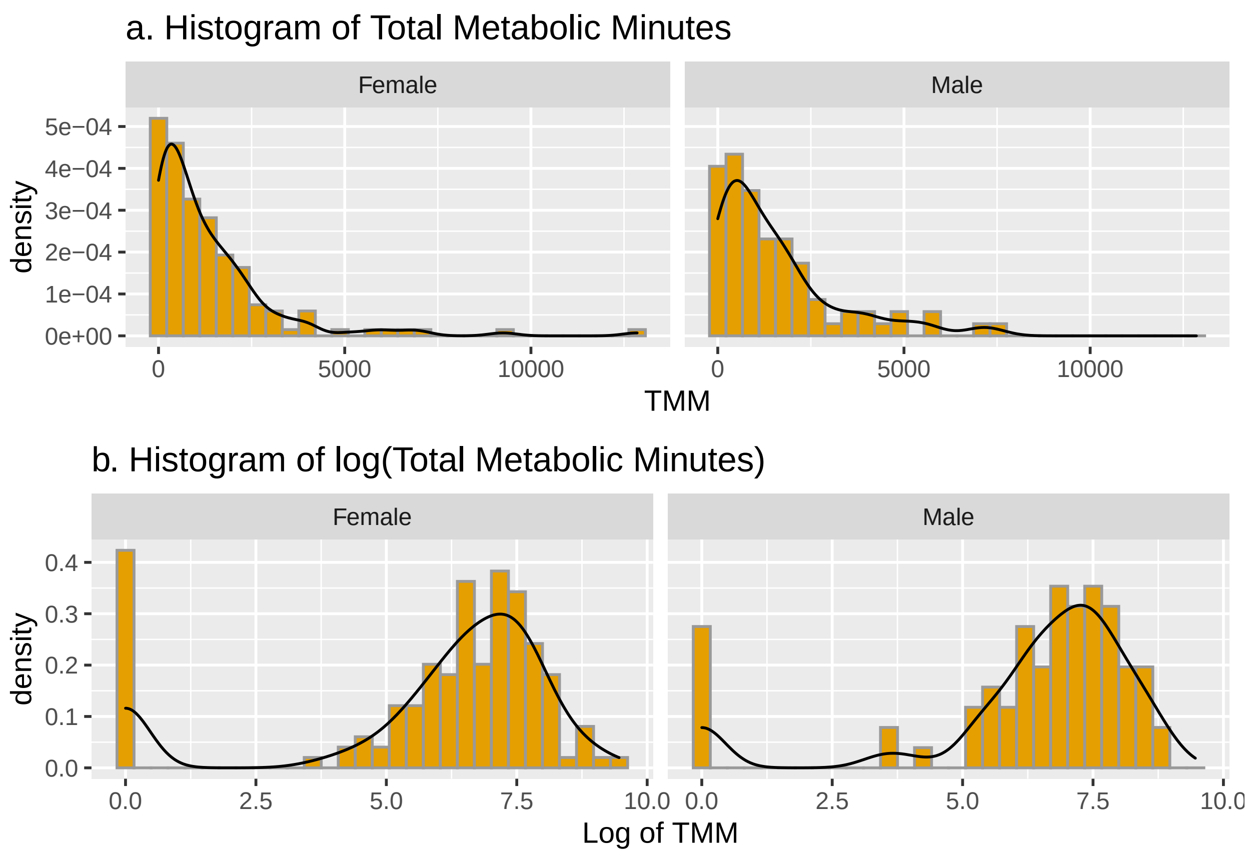

Figure 2: The above show histograms of Total Metabolic Minutes with overlayed density curves. A shows TMM is right-skewed and may benefit from a transformation, while B shows that the transformation helps the skew but is bi-modal with an additional peak at 0.

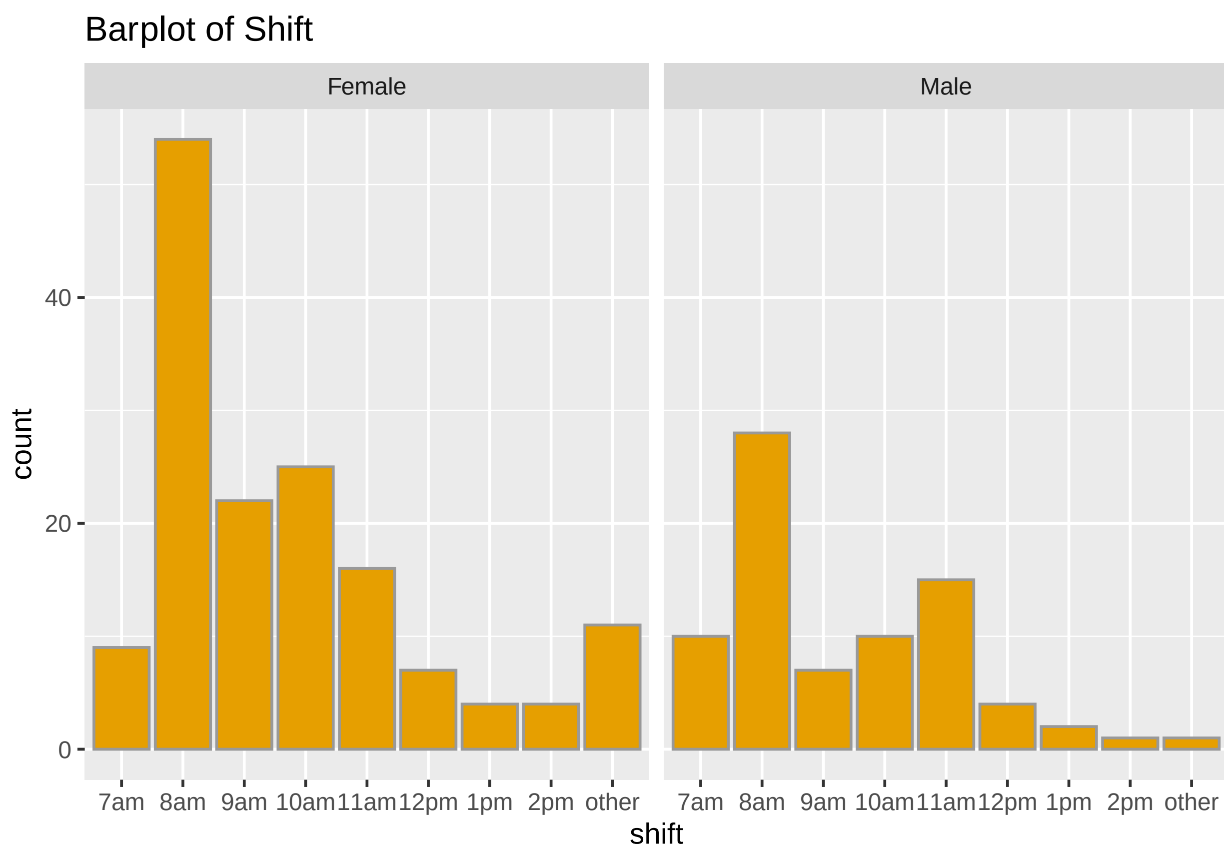

Figure 3: Number of employees in each shift displayed. May want to make into an ordinal variable, as 7am is objectively earlier than 8 am, etc.

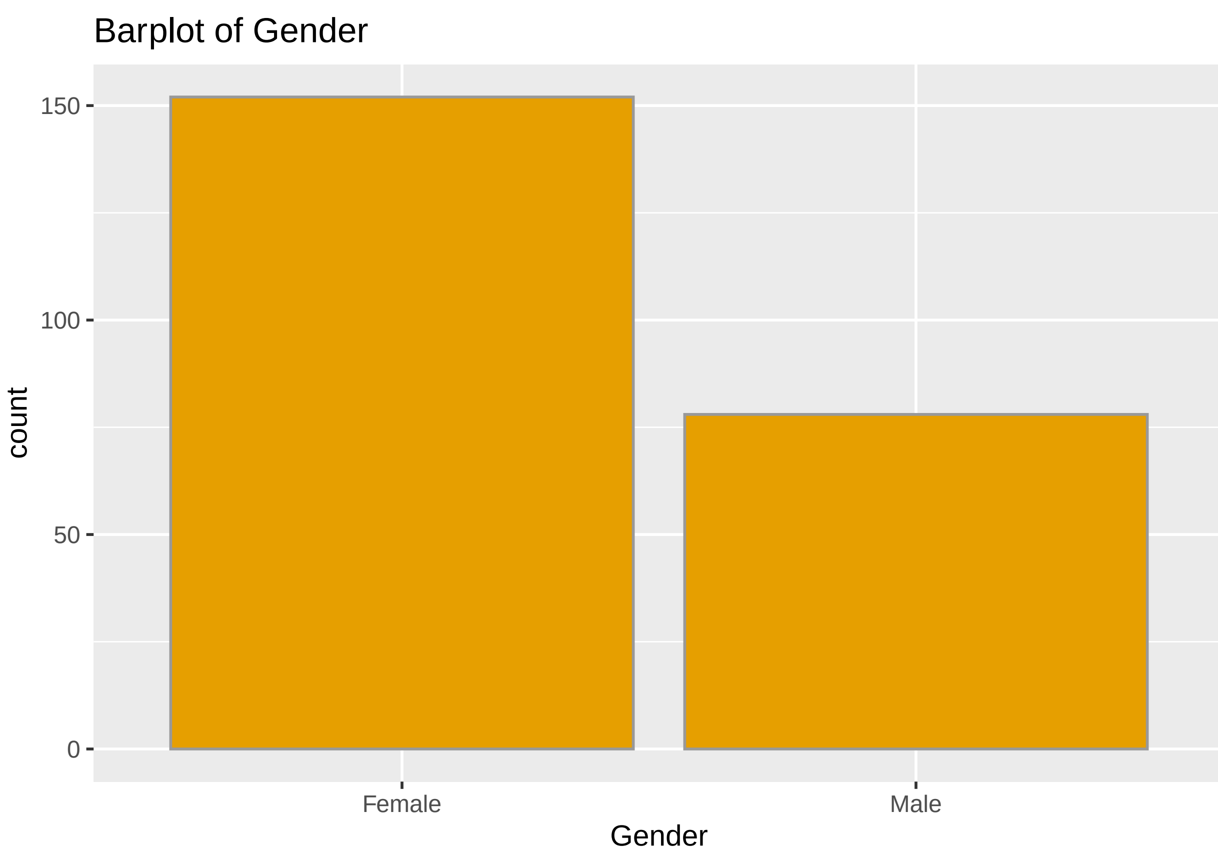

Figure 4: Number of employees identifying as each gender

Figure 5: The above show histograms of age with overlayed density curves. A shows age is right-skewed, while B shows that the transformation helps the skew but only to a limited extent. Transformation may not be necesarry

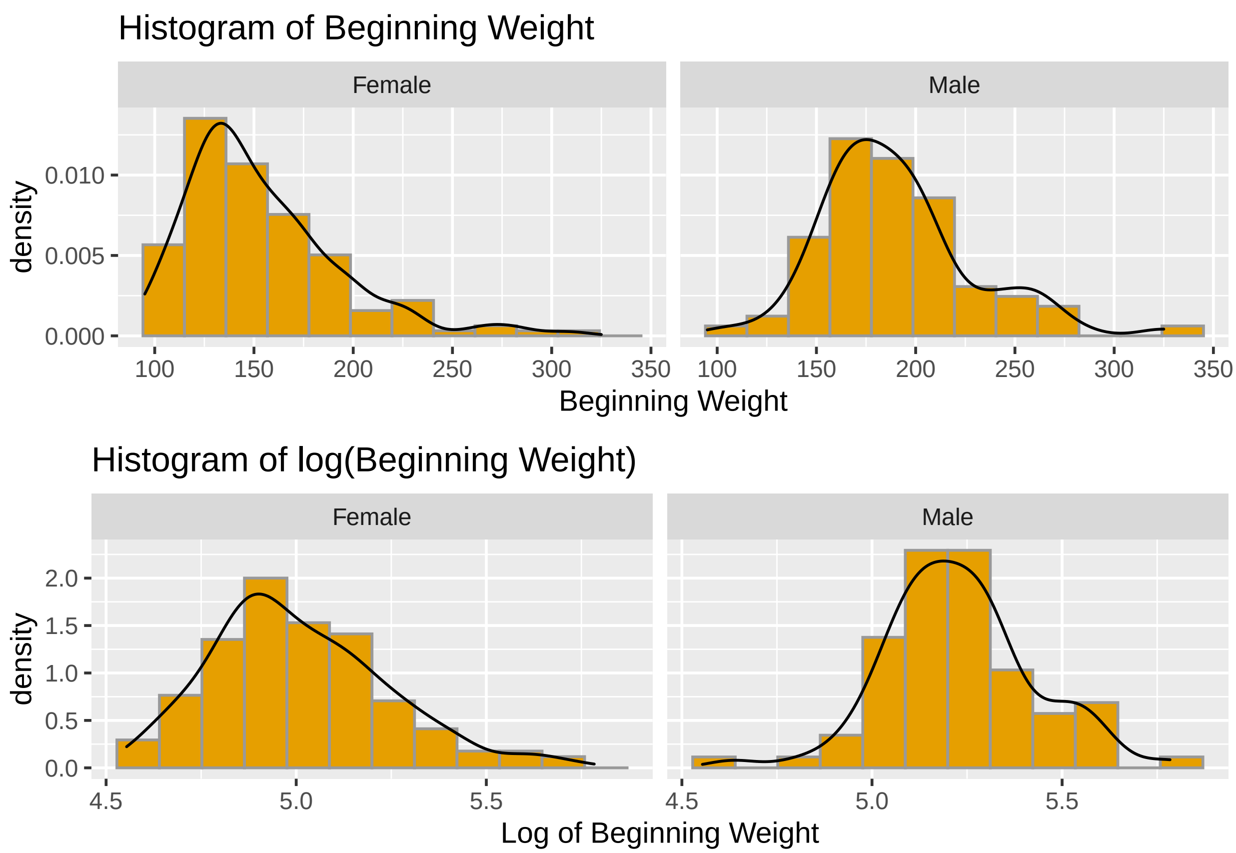

Figure 6: The above show histograms of beginning weight with overlayed density curves. A shows that beginning weight is right-skewed, while B shows that the transformation helps the skew but only to a limited extent. Transformation may not be necesarry, since the skew was not very pronounced initially.

4 Checking for Interactions

After performing a log-transformation on total metabolic minutes, the final step towards fully specifying our model is to decide whether or not to model interactions. We plotted scatter plots of pounds gained versus each variable by shift, and then by gender to check for potential interaction with shift and gender. If the slopes for different shifts or each gender were clearly distinct, then we included an interaction. Those two variables were chosen to analyze since they are the factors and if a health program were designed to target specific shifts or a specific gender then its effects could be predicted reasonable well.

4.1 Interaction between Predictors and Shift

For all three plots (Figures 7-9), the slopes withing shifts were clearly different in both magnitude and direction, so interactions with shift are modeled for all three of TMM, age, and beginning weight.

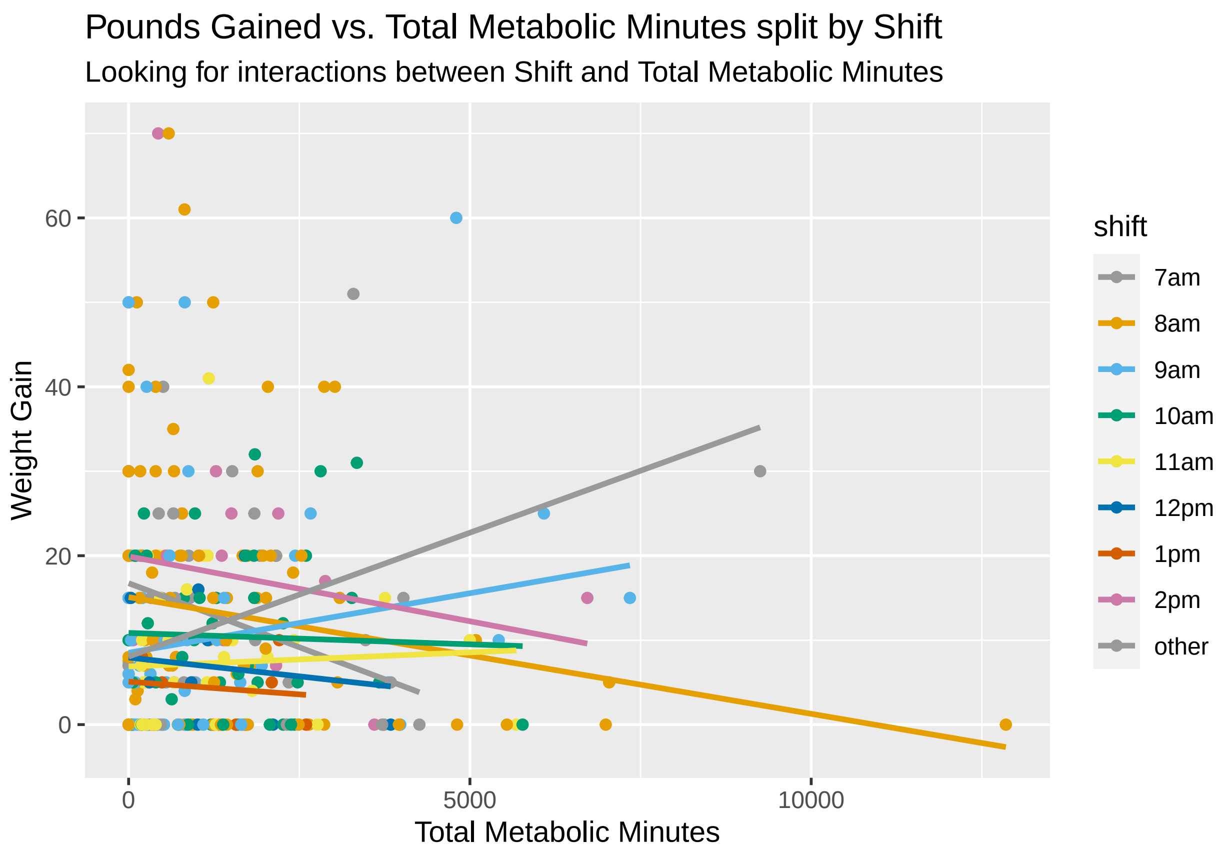

Figure 7: This plot illustrates the correlation between weight gained (in pounds) against exercise time (in TMM), with lines of best fit for each shift. We see markedly different slops depending on the shift, so an interaction should be included in the model.

4.2 Interactions between Predictors and Gender

Overall, the plots for interactions with gender (Figures 10-13) show less substantial divergence than we saw above for interactions with shift, but they still seem to be present with TMM, shift, and beginning weight. The interaction between TMM and gender seems to be that mean are more likely to gain less weight with more exercise than women. Likewise for shift, men seem to gain less weight with later shifts while women are not affected by shift changes alone. There does not seem to be any meaningful difference between men and women of different ages, as the slops are very close and essentially parallel. Regarding beginning weight,

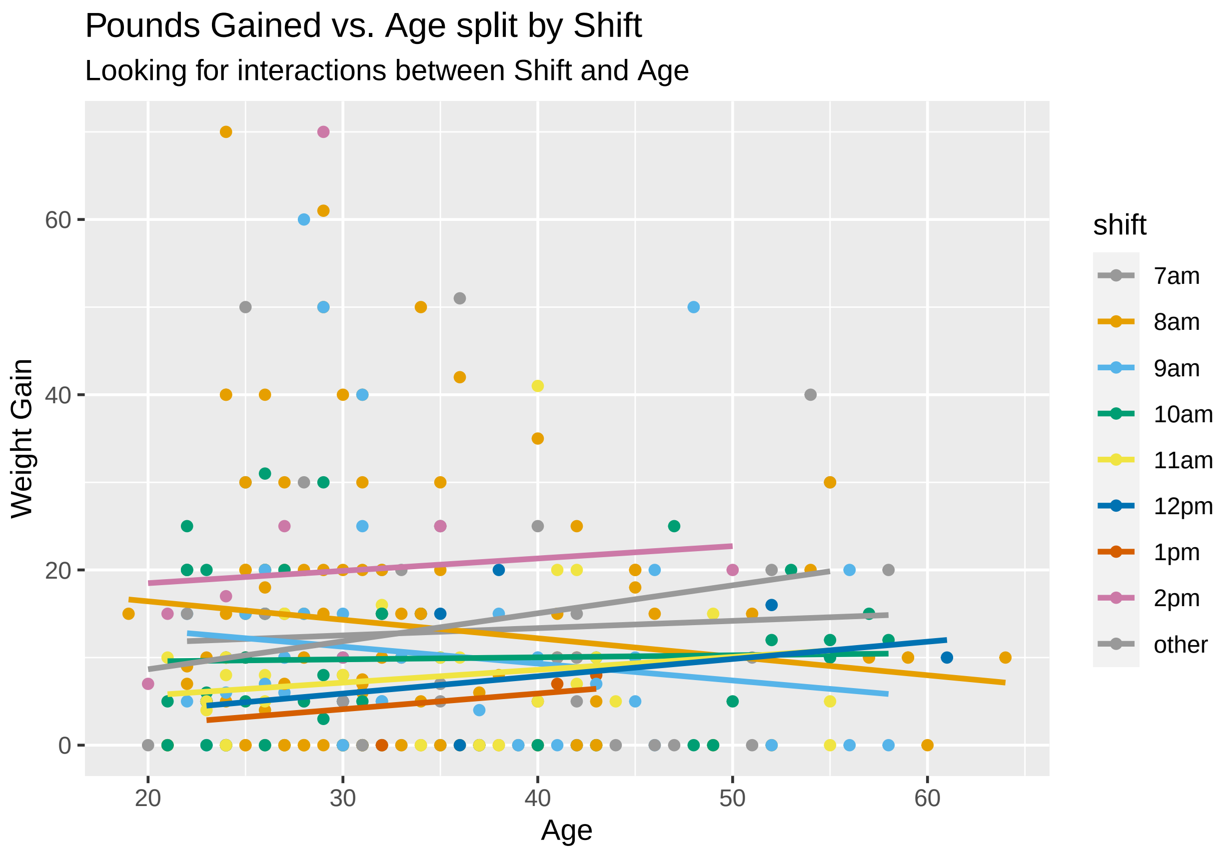

Figure 8: This plot illustrates the correlation between weight gained (in pounds) against age (in years), with lines of best fit for each shift. We see different slops depending on the shift, so an interaction should be included in the model.

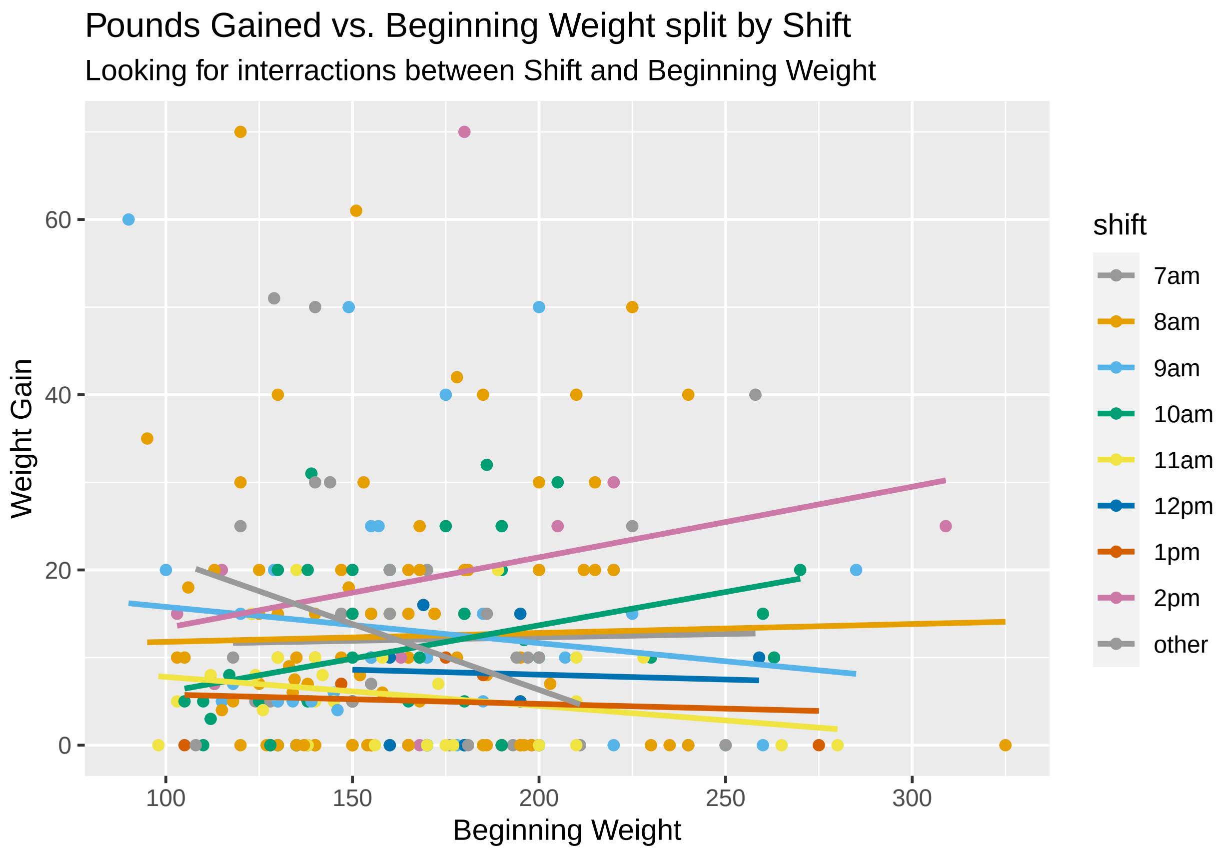

Figure 9: This plot illustrates the correlation between weight gained (in pounds) against beginning weight (in pounds), with lines of best fit for each shift. We see different slops depending on the shift, so an interaction should be included in the model.

men appear to be more likely to gain weight when they start from a higher weight, while again women seem unaffected.

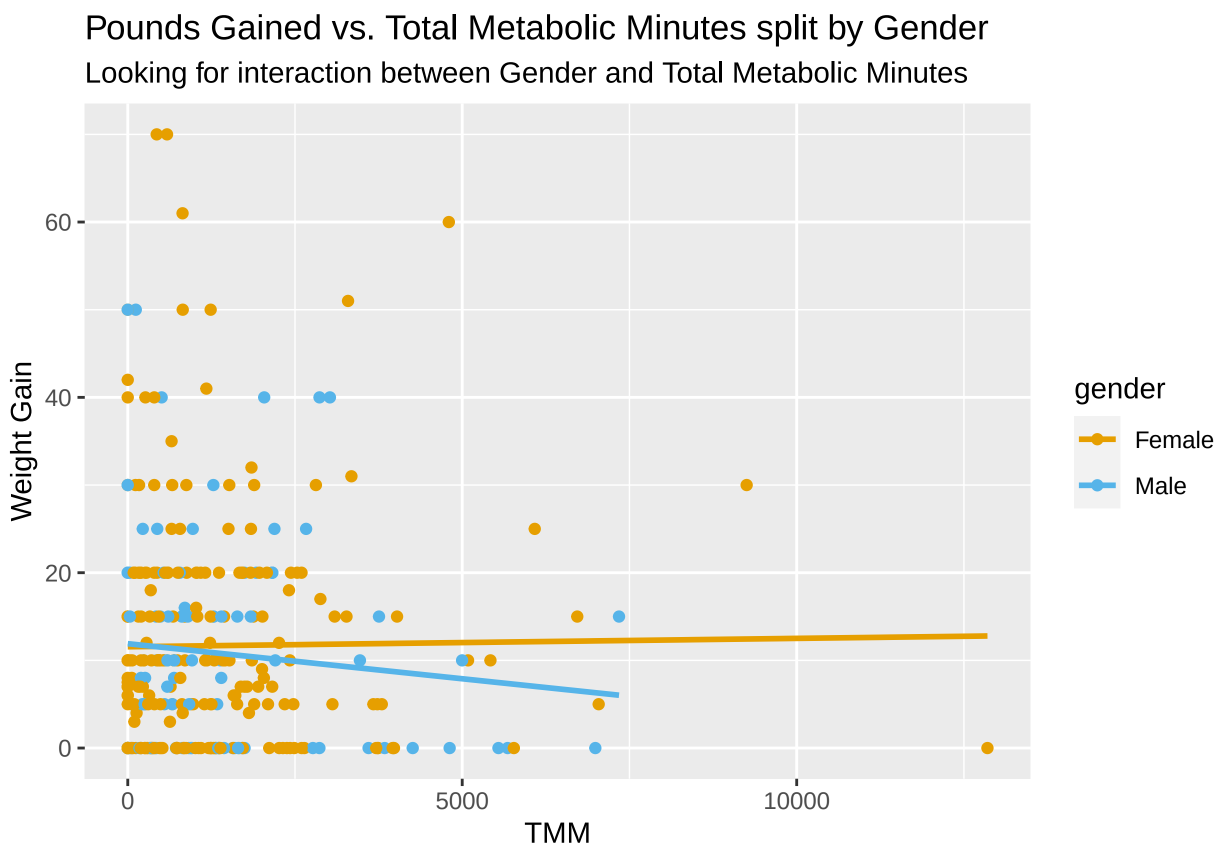

Figure 10: This plot illustrates the correlation between total metabolic minutes and pounds gained per individual. We do see a difference in slopes between males and females. For males we see a negative interaction between the two variables. As total metabolic minutes increase, pounds gained decreases as we expected. For females, we see much more dispersion and the slope seems pretty close to zero.

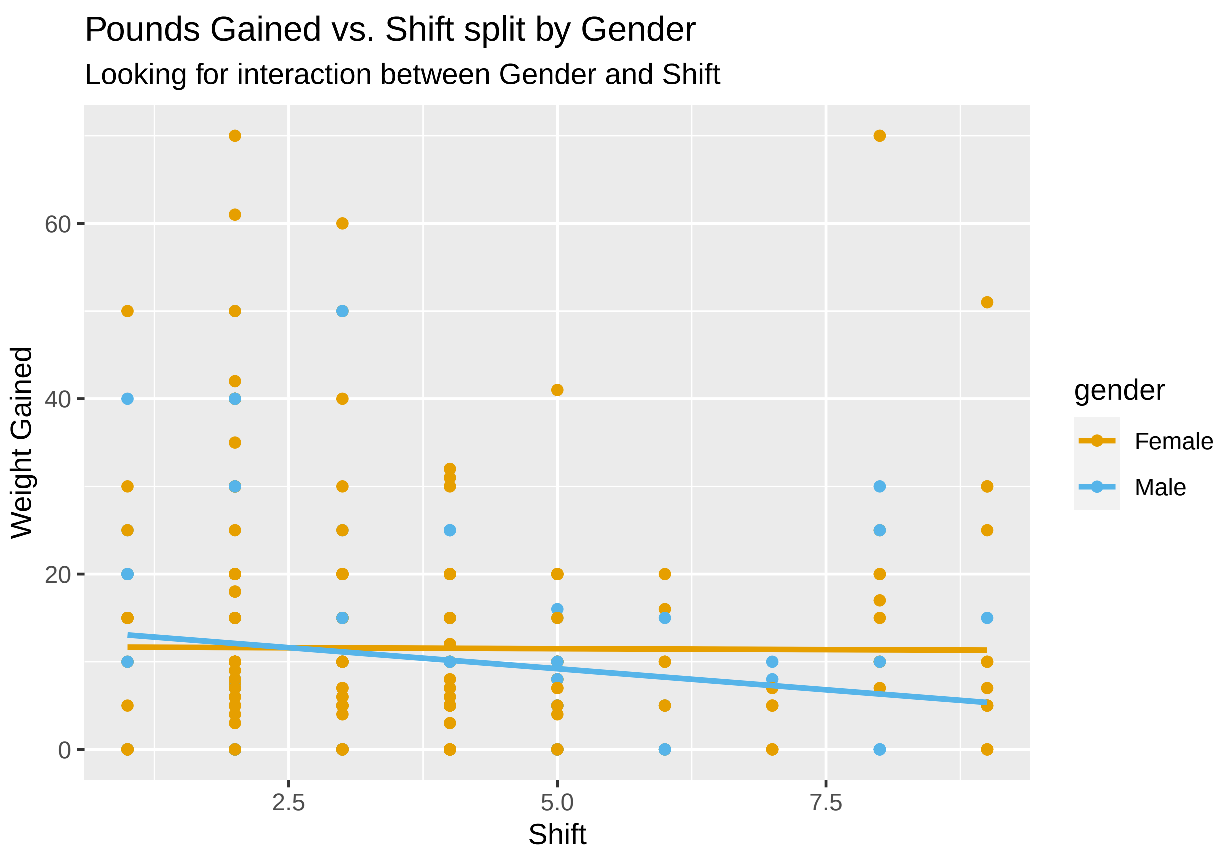

Figure 11: This plot illustrates the correlation between the start time of the individual's work shift and pounds gained per individual. The shift is treated as an ordinal variable for the line of best fit to be rendered. For males, we can see a negative slope indicating that the later the shift starts the less weight they will gain. For females, again, we see more dispersion and less of a correlation between shift and weight gain.

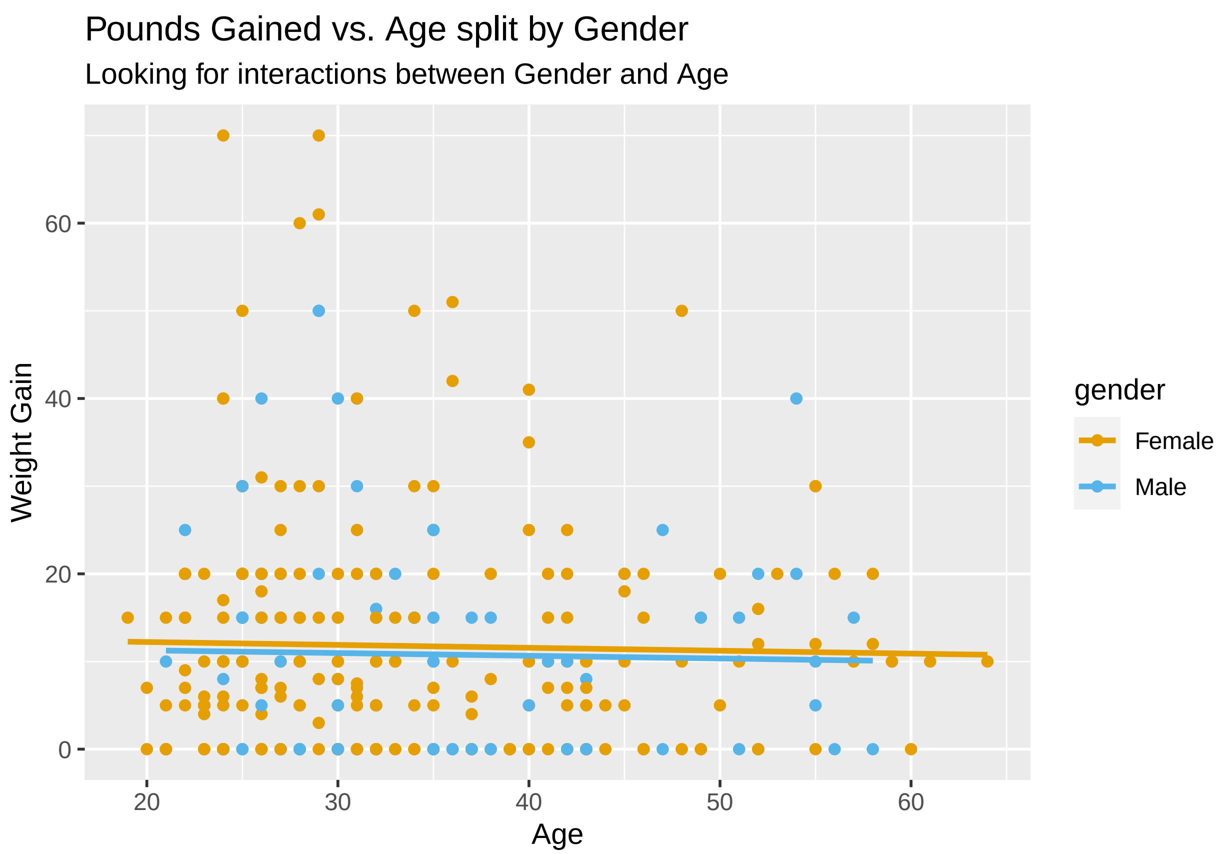

Figure 12: This plot illustrates the correlation between the age of the individual and pounds gained per individual. Both males and females seem to have a pretty similar slope that is close to zero. This tells us that age by itself does not tell us much about weight gain for males or females and no interaction appears to exist.

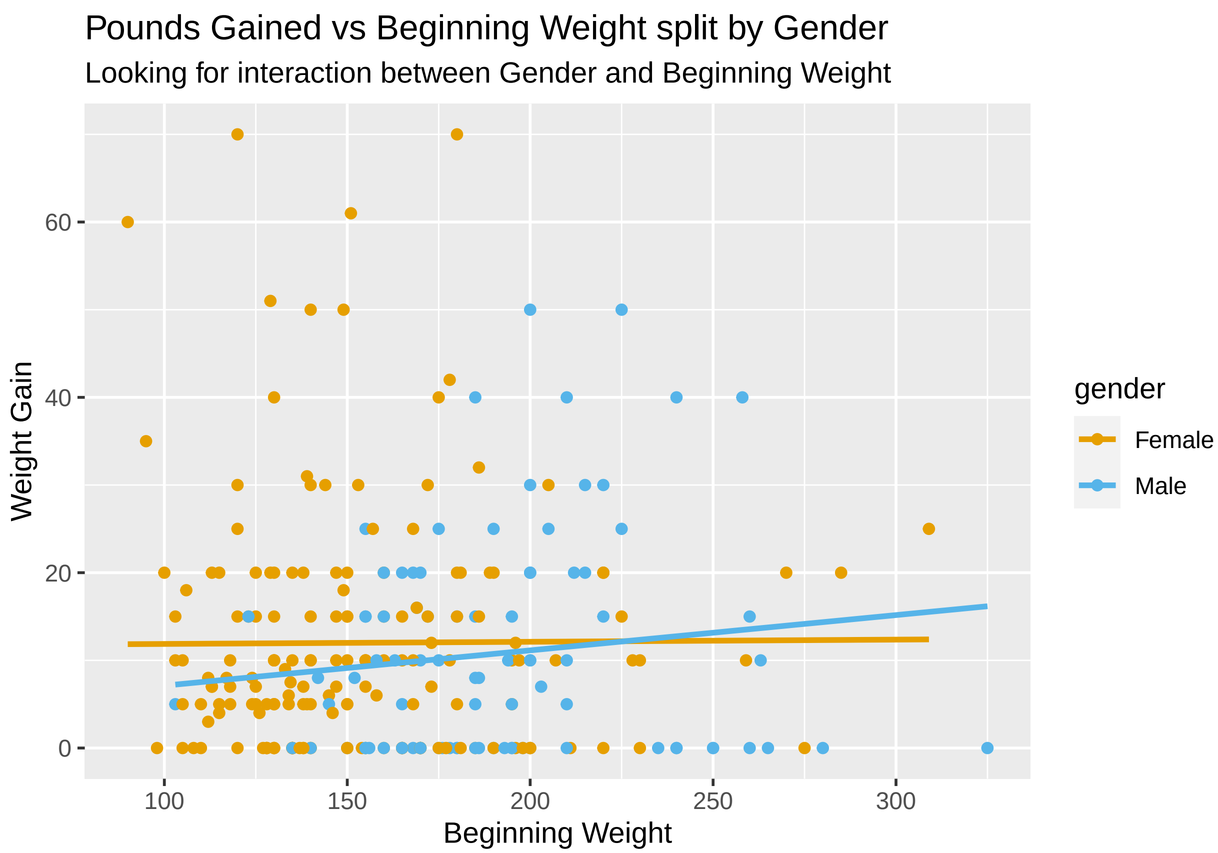

Figure 13: This plot is showing the correlation between an individual's body weight at the beginning of this study against how much weight they have gained at the end. Now, we see a positive slope for males and a slope close to zero for females.

5 Final Analysis Population

5.1 Missing Values

The complete data set nominally includes 392 observations, but with 44 observations missing from the response variable. Since we are attempting to model this response, there is no meaningful way to impute the missing values, and they have been omitted. From there, missing values for TMM can be be calculated for rows where walk, moderate, and vigorous exercise times are known. Finally, the rest of the missing values should not be calculated since we cannot determine a structural reason for missingness, and the distributions were all fairly skewed —so replacement with mean observations could bias our results. After omitting rows with missing values, we are left with 238 observations, which should be sufficient for estimating effects.

5.2 Outliers

In a data set this large, there are bound to be some extreme cases. It is more useful to try and explain how weight gain behaves for the *vast majority* of people than it is to try and explain every single observation. So, for good practice, we will ignore any observations that we deem too extreme. Figure 14 identifies some of the most extreme values for weight gain by gender, with 8 observations falling outside of 1.5*IQR above and below the third and first quartiles, respectively.

After the 8 extreme cases are removed, there remain two observations that qualify as outliers by the IQR rule (Figure 15). However, these two values (females gaining 40 and 42 pounds) would be well within the range of the IQR rule if they were in the “other” shift category. Because of this, removing these values feels like too aggressive of a maneuver at this juncture, so we will leave those two observations in.

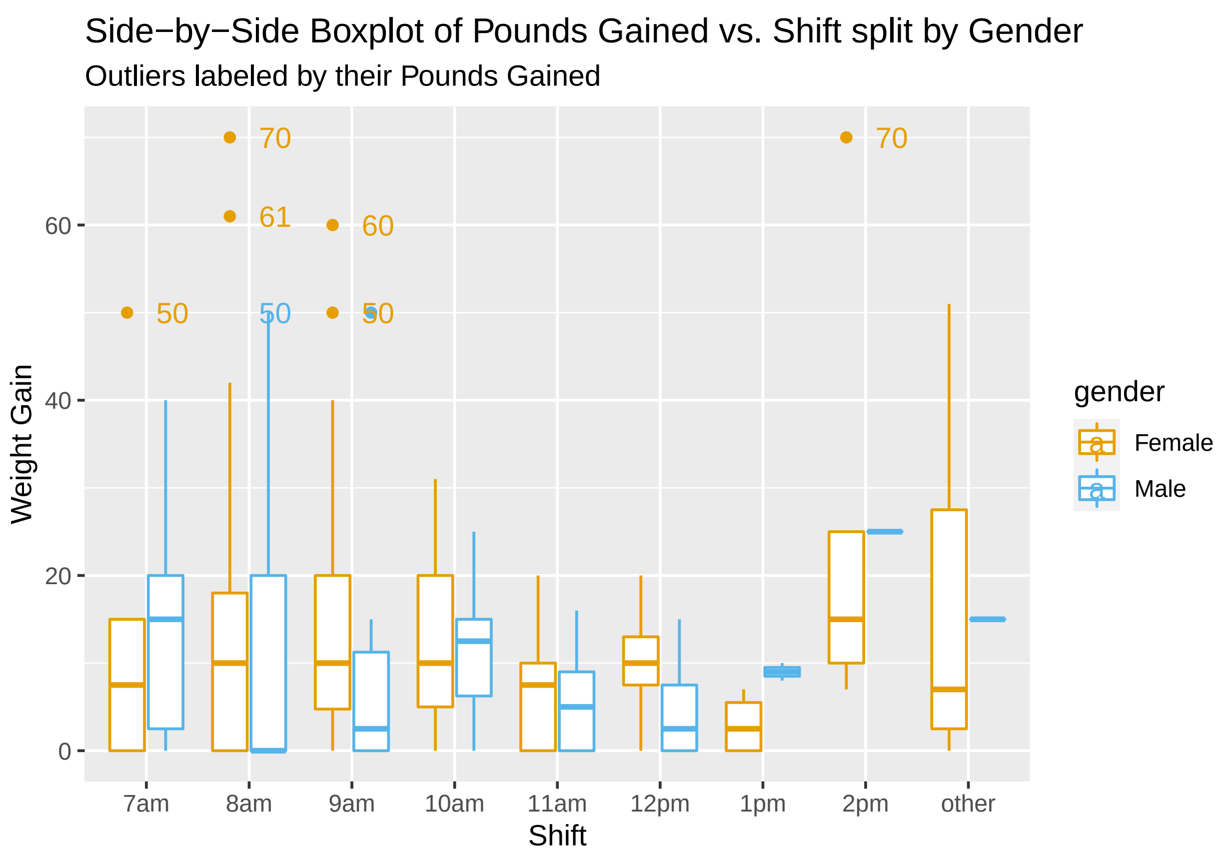

Figure 14: We see here 8 observations that count as outliers in their group. Each of the values would have been at least borderline outliers in any other group as well, reassuring us that removing them is appropriate.

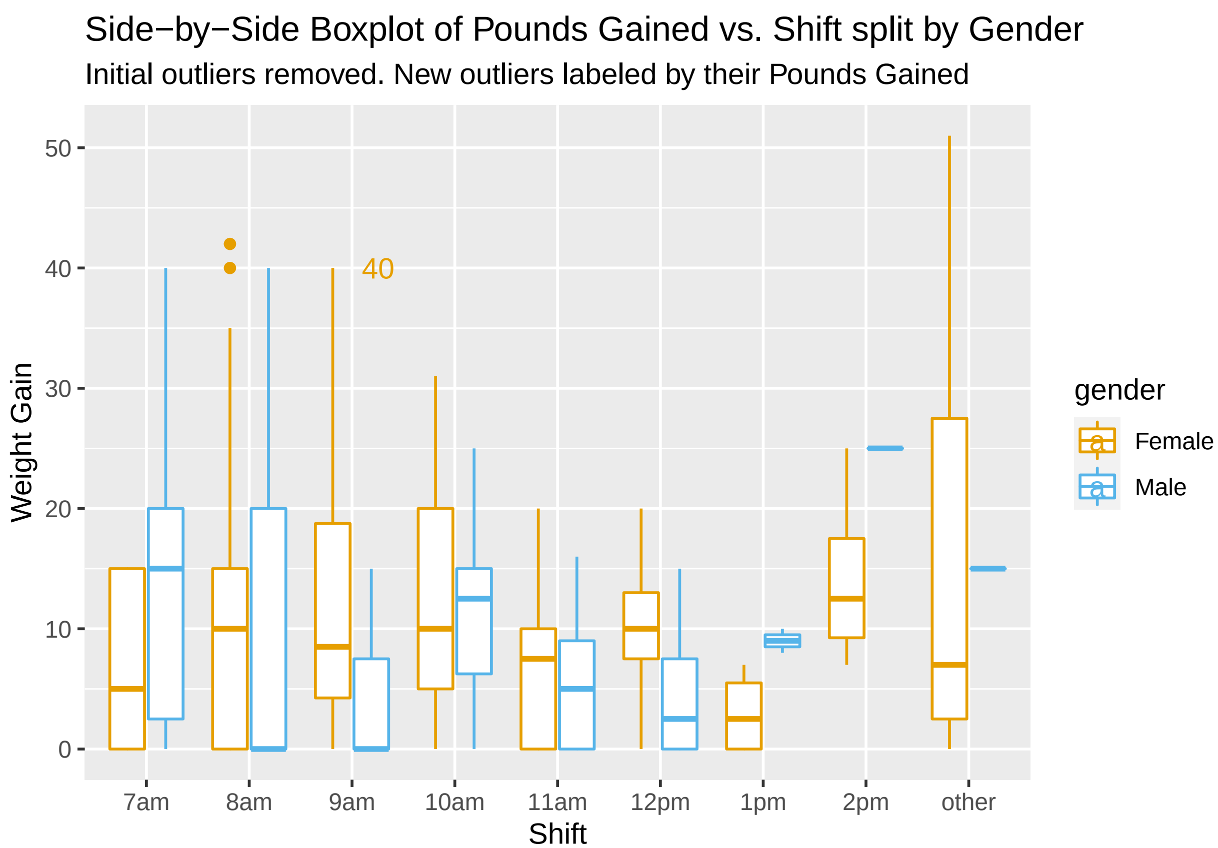

Figure 15: Only two outliers remain after removing the first eight. However, these would not be outliers if they fell into the category shift = `other`, enticing us to leave them in.

6 ZIP Model

In attempting to model weight gain, numerous options are available. We could have modeled the response variable of pounds gained by using a variety of well-known parametric distributions that are used to model severity in the insurance world, such as the Gamma, Pareto, Weibull, Lognormal, Generalized Beta, or any other parametric distribution commonly used to model right-skewed continuous random variables. However, just knowing that weight gain in this scenario follows a common distribution doesn't provide us with any information as to what *drives* weight gain. An additional option of treating the response of weight gain as a censored version of normally-distributed weight change was also considered; however, the non-normality of pounds gained for those who did gain weight discouraged us from this (Figure 16).

Ultimately, we settled on a zero-inflated Poisson model, which uses a logit-link to the binomial for determining if an employee crosses the threshold of gaining weight, and then a log-link to the Poisson for determining the number of pounds gained once the threshold is crossed. We feel comfortable violating the assumption of discrete counts typically expected of a Poisson distribution since most responses were reported in integer values (those that were not were rounded for the analysis), and counting the number of pounds gained since the beginning of the study (i.e. over a fixed eight-month period) is a reasonable interpretation of the response. The zero-inflation estimates can then account for the respondents who did not gain weight.

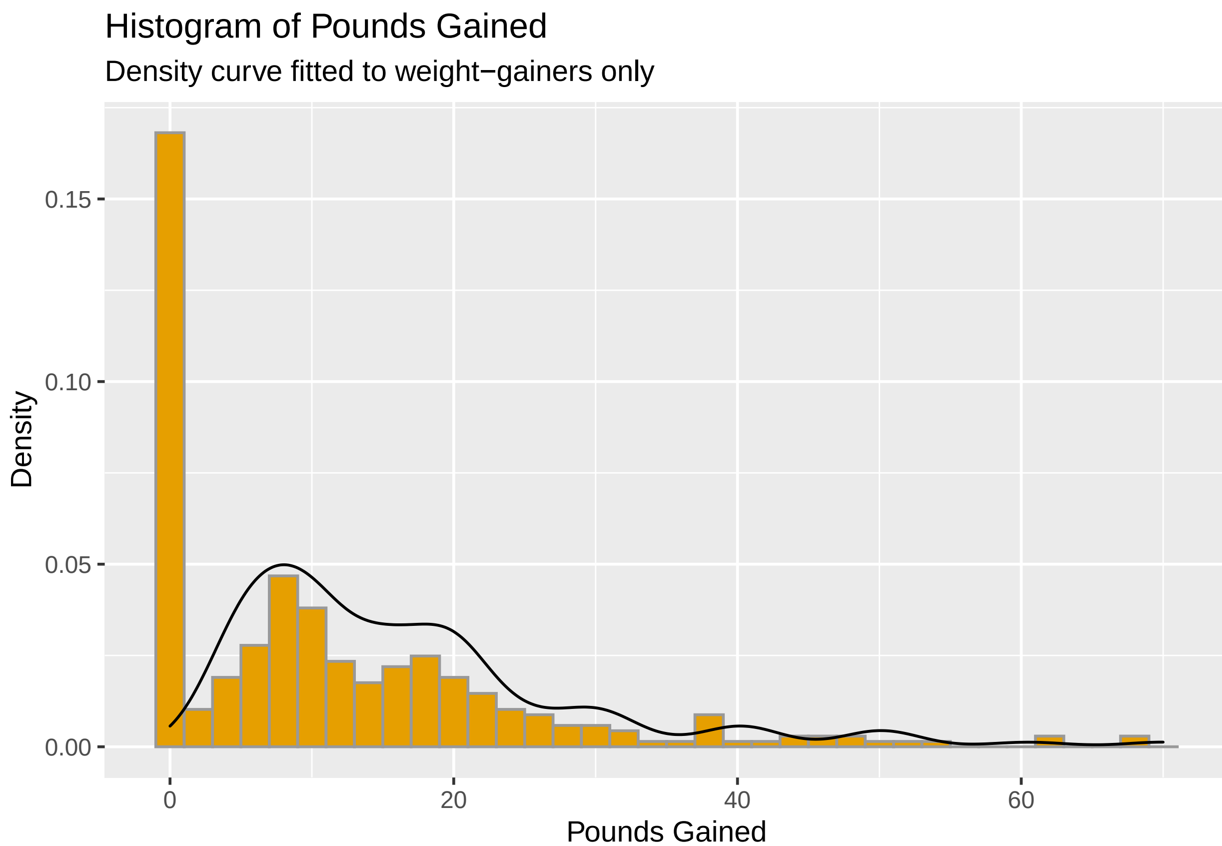

Figure 16: The above histogram shows the densities of pounds gained for employees at the call center, while the overlayed density curve shows the emperical density curve of pounds gained amongst emplyees who reported gaining weight. The pounds gained have been uniformly jittered for the non-zero responses to smooth some peaks at multiples of 5. The high proportion of respondents who did not report gaining weight indicates that a higherarchical model differentiating between those who gained weight and those who did not may be appropriate. The long right tail of the density curve indicates that a Poisson GLM may be appropriate to model the pounds gained amongst those who reported weight gain.

6.1 Regression Results

The coefficient estimates for the Poisson portion of the model are interpreted as the effect of increasing the predictor values by one unit on the log of the mean of weight gained, while the coefficient estimates for the binomial portion represent the effect of increasing the predictor by one unit on the log odds of gaining weight.

The results of our regression on the full data set (Table 1), and on the data set without outliers (Table 2) give very similar topline results. They both indicate that shift and total metabolic minutes may influence the amount of weight gained by respondents who gain weight, but they probably do not affect whether or not the respondent gains weight. Shift has a negative impact on the amount of weight gained, so respondents who work later gain less weight, and the interaction of shift on gender indicates that this negative relationship is stronger for men than women. Total metabolic minutes also decreases the count of pounds gained on average, and this effect is likewise stronger in men than in women. Taken together, the interaction of shift and total metabolic minutes is weaker as the shift gets later.

The effect of gender on weight gain is not significant, but indicates that men may gain less weight than women overall. The effect of beginning weight is significant in the model without outliers, but very small, and insignificant in the full data model. The interaction of the two, however is significant and indicates that men with higher beginning weights gain more weight. In contrast to beginning weight, age is significant in the full data model, but it is very small, and its significance disappears in the model without outliers. The interaction between shift and beginning weight is not significant in either model.

The log-likelihood of the model without outliers is higher than that of the full data model, so we propose that the estimates from the model without outliers be used to predict the effects of any proposed intervention on people who are gaining weight. Neither model can be used to identify employees who may be at risk for gaining weight, or to estimate the effect of an intervention to reduce such risk. There maybe some unidentified variable dictating who gains weight, but that is an area for future research.

6.2 Poisson Diagonistics

The Poisson distribution assumes that mean and variance are dictated by the same parameter, so a well specified model would show roughly equal estimates of mean and variance, with variance estimated as the squared residuals. Figure 17 shows that mean and variance are proportional in the Poisson portion of the model with outliers, but there seems to be some overdispersion, since the variance tends to fall above the reference line. We can see that fitting the model without outliers effectively reduces the overdispersion for a close fit, despite three observations with particularly low variance estimates.

A well specified model should also show residuals following a half-normal distribution plot (since count data cannot be negative). Figure 18 indicates that the full data model has some deviation from half-normal residuals in the center and at the right tail. The model estimated without outliers performs much better and does not deviate from half-normal quantiles until the final 7 observations.

Finally, there should be no pattern in the residuals of a well-specified model. Figure 19 shows widely dispersed residuals in the full data model, but they still center around the null reference line. The model without outliers has residuals much more compactly centered around the reference line. Both of these plots show some patterns in the residuals in the form of lines. These are most likely a result of the large number of respondents who gave the same number of pounds gained, and the model giving them different estimates.

Overall there do not seem to be any issues with our model specification that indicate our results may be unreliable, or that the model is misspecified, however, the model without outliers again outperforms the full data model in ever aspect, and its estimates should be taken as the final result of this analysis.

Table 1: Coefficient Estimates for a Zero-Inflated Poisson Model on the Full Data Set

Poisson Model with Log Link:				
Variable	*Coefficient*	Std. Error	z -Score	p-Value
Intercept	3.675	0.298	12.323	1.900×10^{-16}
Shift	-0.304	0.056	-5.429	5.670×10^{-8}
Log of Total Met Min	-0.096	0.018	-5.207	1.920×10^{-7}
Male	-0.373	0.292	-1.276	0.202
Beginning weight	-0.000	0.002	-0.255	0.799
Age	-0.005	0.002	-2.271	0.023
Shift:log of Total Met Min	0.035	0.005	6.650	2.944×10^{-11}
Shift:beg weight	0.0004	0.000	1.802	0.072
Shift:Male	-0.113	0.024	-4.626	3.720×10^{-6}
Male:log of Total Met Min	-0.038	0.017	-2.231	0.026
Beginning Weight:Male	0.005	0.001	3.739	1.840×10^{-4}
Zero-Inflation Binomial Coefficients with Logit Link:				
Intercept	-0.570	1.951	-0.292	0.770
Shift	-0.051	0.442	-0.115	0.909
Log of Total Met Min	0.005	0.117	0.041	0.967
Male	-0.197	1.713	-0.115	0.909
Beginning weight	0.001	0.012	0.046	0.963
Age	-0.007	0.015	-0.449	0.654
Shift:log of Total Met Min	-0.028	0.029	-0.965	0.334
Shift:beg weight	0.001	0.003	0.275	0.783
Shift:Male	-0.047	0.176	-0.268	0.789
Male:log of Total Met Min	0.096	0.120	0.797	0.425
Beginning Weight:Male	0.002	0.008	0.194	0.846
Log-likelihood:	-1115	on 22 Degrees of freedom		

Table 2: Coefficient Estimates for a Zero-Inflated Poisson Model without Outliers

Poisson Model with Log Link:				
Variable	*Coefficient*	Std. Error	z -Score	p-Value
Intercept	3.147	0.298	0.329	$< 2.0 \times 10^{-16}$
Shift	-0.356	0.056	0.072	6.60×10^{-7}
Log of Total Met Min	-0.145	0.018	0.025	3.91×10^{-9}
Male	-0.432	0.292	0.319	0.175
Beginning weight	0.004	0.002	0.002	0.036
Age	-0.001	0.002	0.002	0.680
Shift:log of Total Met Min	0.055	0.005	0.008	2.81×10^{-13}
Shift:beg weight	-0.0001	0.000	0.0002	0.415
Shift:Male	-0.133	0.024	0.028	1.42×10^{-6}
Male:log of Total Met Min	0.015	0.017	0.021	0.486
Beginning Weight:Male	0.004	0.001	0.002	0.007
Zero-Inflation Binomial Coefficients with Logit Link:				
Intercept	-0.269	2.128	-0.126	0.899
Shift	0.028	0.487	0.057	0.954
Log of Total Met Min	0.057	0.140	0.406	0.685
Male	-0.372	1.768	-0.210	0.833
Beginning weight	-0.003	0.013	-0.220	0.826
Age	-0.012	0.017	-0.687	0.492
Shift:log of Total Met Min	-0.048	0.038	-1.282	0.200
Shift:beg weight	0.001	0.003	0.408	0.683
Shift:Male	-0.033	0.196	-0.169	0.866
Male:log of Total Met Min	0.061	0.130	0.469	0.639
Beginning Weight:Male	0.004	0.009	0.478	0.633
Log-likelihood:	-767.7	on 22 Df		

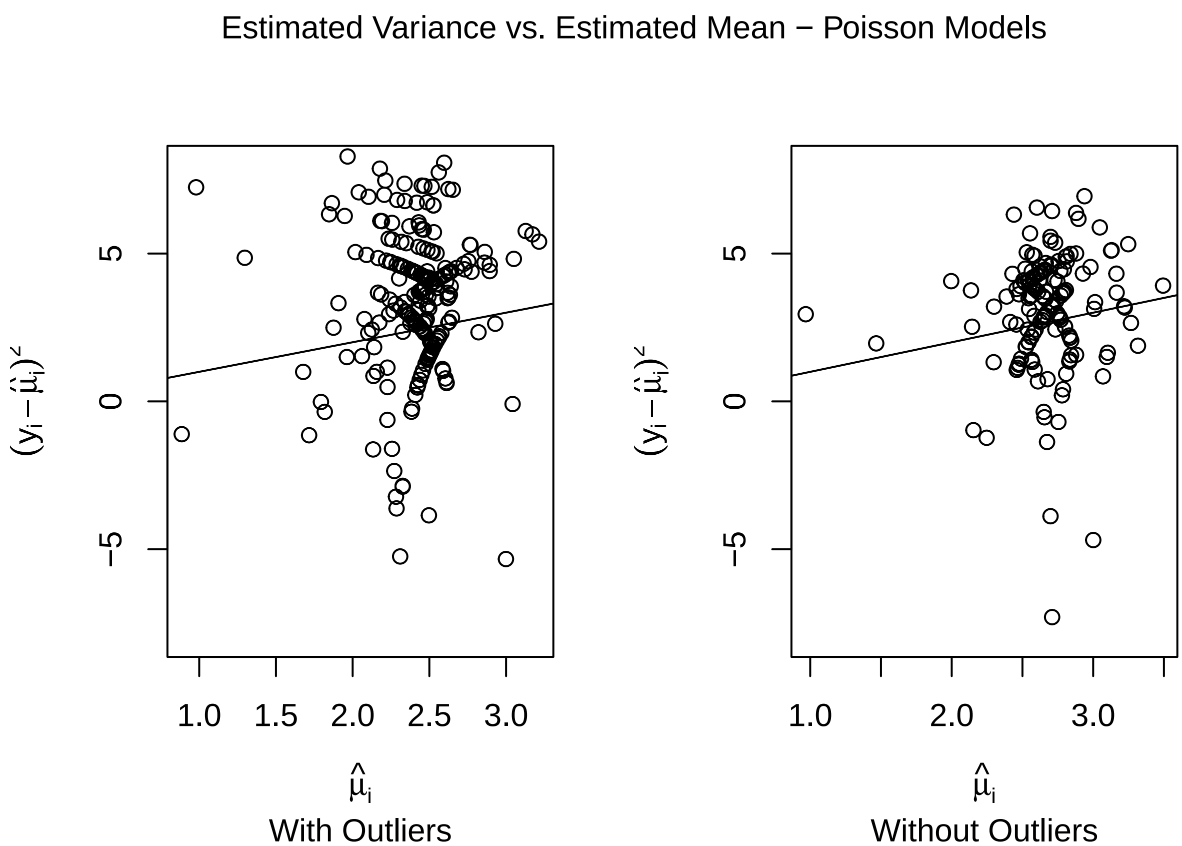

Figure 17: These plots show the estimated variances and means of a poisson distribution for each observation. One of the assumptions behind a Poisson is that the mean ia equal to the variance. The model with outliers seems to have mean proportional to variance, but slightly less, while the model without outliers looks like a good fit.

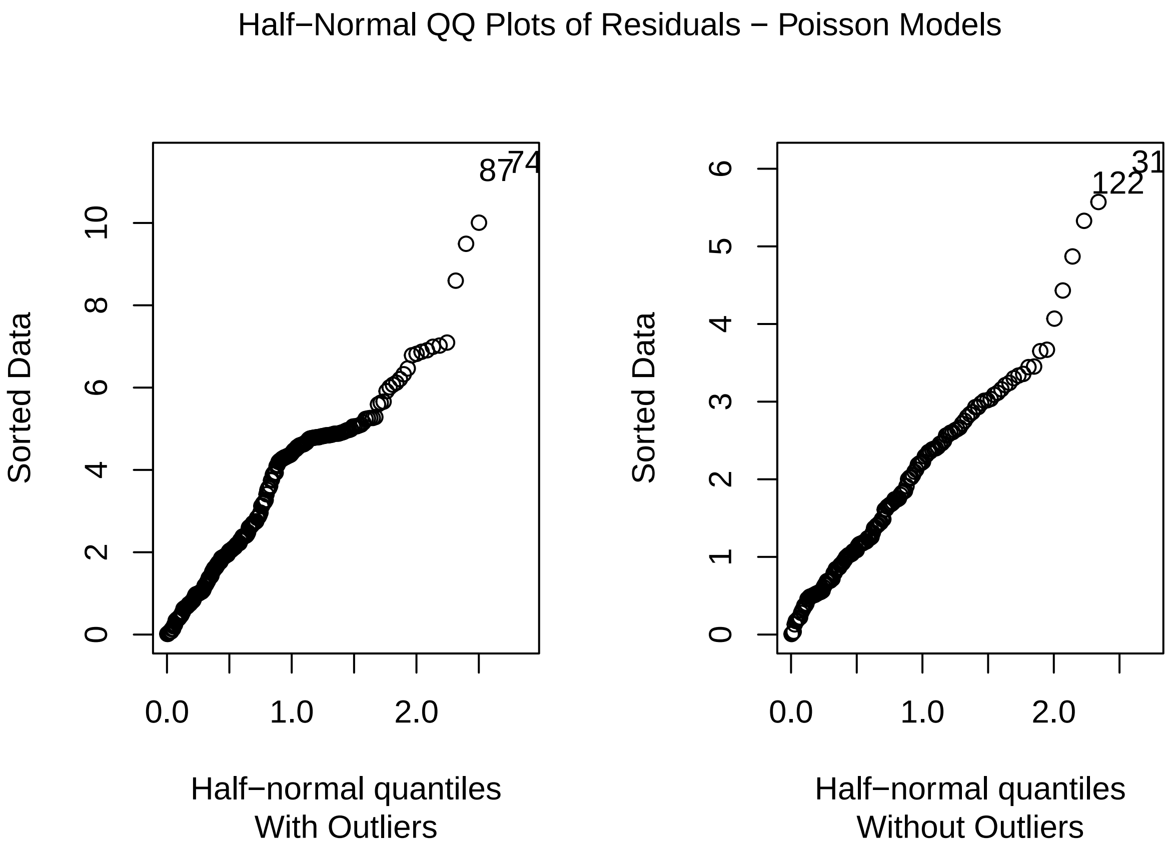

Figure 18: These half-normal plots are used to assess the distribution of the residuals. The model with outliers has a decent fit, but deviates somewhat in the middle and right-tail. The model without outliers fits very well.

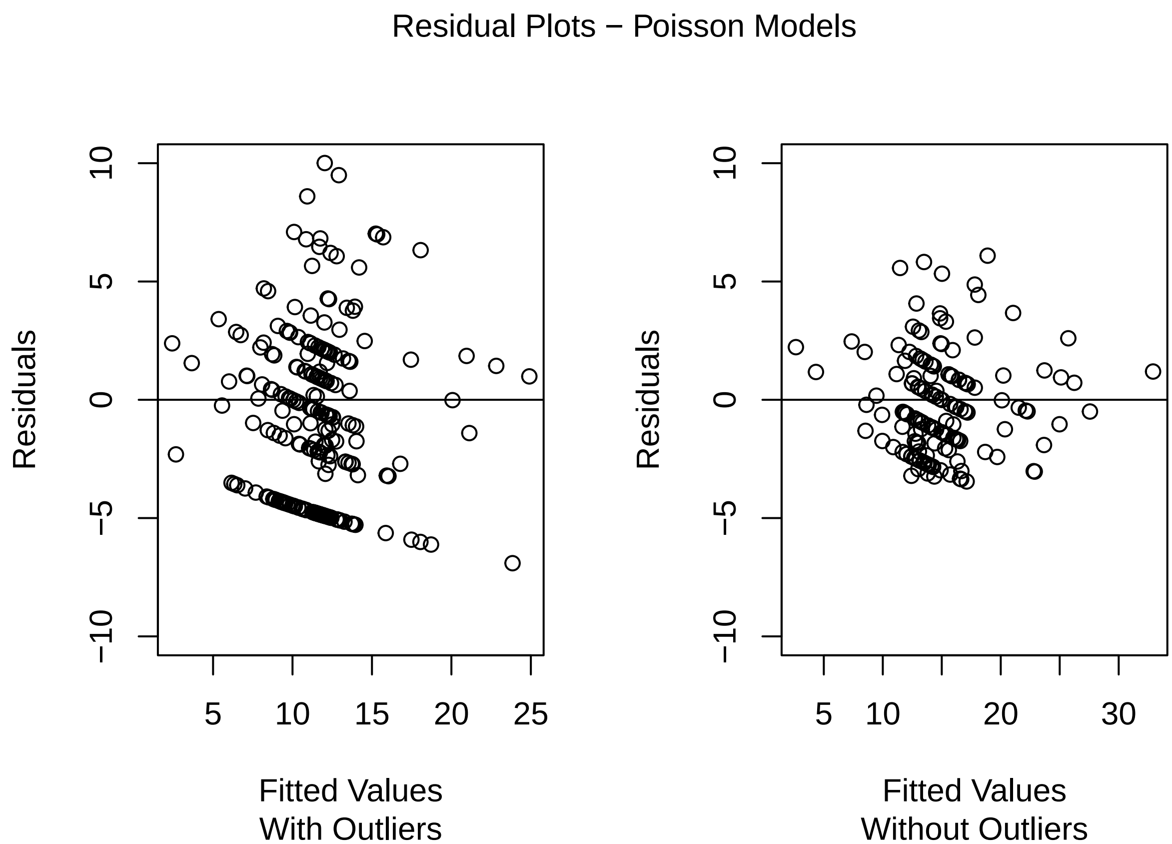

Figure 19: The residual plots show no obvious deviations from the null line. The plot with outliers shows some substantial dispersion, but the residuals without outliers are tightly clustered around the null line.

References

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