MATERNAL SMOKING AND BIRTH WEIGHT

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1 Introduction

We want to investigate the effect of maternal smoking on infant birth weight and gestation period. We will begin by discussing previous literature on the topic. Overall, the results seem to be unanimous.

A study published by the British Medical Journal in 1972 found that smoking cigarettes caused birth weight to fall by 170 grams and increased late fetal and neonatal mortality rate by 28%. Furthermore, the study showed that if a mother changed her smoking habits by the 4th month of pregnancy, the weight loss would be much less drastic. Mothers who went from smoking 20-30 cigarettes per day to 0 per day had babies whose average weight was 3,335 grams, whereas mothers who continued to smoke at such a rate had babies whose weight averaged 3,179 grams. In comparison, mothers who didn't smoke before pregnancy *or* after the 4th month had babies whose average weight was 3,387 grams. Even after controlling for possible confounding variables such as social class, maternal age, maternal height, and others, the difference was found to hold[3].

We see similar findings in a study published by Mary Sexton and J. Richard Hebel in 1984. The study intended to investigate whether changes in smoking habits during pregnancy would affect birth weight. The authors claimed "[their] clinical trial results are the first... from a prospective, randomized, and controlled experiment demonstrating that a reduction of smoking during pregnancy improves the birth weight of the infant"[5].

Research has also shown a relationship between smoking and gestation time. A study published in the American Journal of Obstetrics and Gynecology in 1990 found that smoking decreased fetal growth and lowered gestational age. In order to reduce confounding variables the study excluded women with no prenatal care, those who were transferred to the institution for delivery, and those with multiple births, fetal deaths, or congenital malformations. Additionally, women with gestational and insulin-requiring diabetes were excluded, since physicians tend towards early devilry for women in this condition. The study found that women who smoked had a lower mean gestational age at birth. The largest difference was found in women aged 31-35 and those whose age was 36 or higher. The difference in gestational mean for these groups was -0.48 weeks and -0.94 weeks respectively. These differences were found to be statistically significant ($p < 0.05$). The study concluded that smoking lowered both fetal growth and gestational age, with these effects becoming significantly greater as maternal age increased. [7]

2 Data

Our dataset comes from the Child Health and Development Studies' records of all births that occurred from women within the Kaiser Health Plan in Oakland, California between 1960 and 1967. The women in the study all shared threes traits: they were a part of the Kaiser Health Plan, they had prenatal care done in the San Francisco area, and they delivered in a Kaiser hospital in Northern California. The babies in the study are all male, all single babies (i.e. no twins, triplets, or more), and they all lived at least 28 days[2]. This data is clearly observational, as there was no treatment performed on any of the subjects. It is also quite specific, which can be both helpful and harmful. The good comes in that we don't have to worry as much about factors that may affect weight, such as gender of the baby. On the other hand, our findings may not generalize very well, as it is hard to claim that something that we found for a group of mothers and children who all shared some important characteristics would apply to a much larger group. Indeed, it would be difficult to say that our findings would even generalize to female babies.

We are using 3 variables out of this dataset. The first is 'smoke', a categorical variable stored as a discrete numerical value of either 0 or 1 corresponding to a mother who doesn't smoke and one who does. The second variable we consider is 'bwt', which represents birth weight. While this is technically stored as a discrete numerical variable, weight is generally considered continuous, and we will treat it as such. Finally, we consider 'gestation', which is the gestation age of the baby, measured from the mother's last menstrual cycle to the date of birth. This, again, while being stored as a discrete numeric value, can be considered continuous as it is a measure of time.

3 Background

Before we begin analyzing the birth weight data we will review the history of this issue, the underlying science of maternity, and the hypothesized scientific explanation on why smoking may affect birth weight.

Before the 1940's, it was believed that no disease or illness possessed by a mother could negatively affect their child. This all changed in 1941 when Dr. Normal Gregg observed an "unusual" number of babies born with congenital cataracts whose mothers had contracted rubella during their first or second month of pregnancy. Since this first observation, a variety of studies have been conducted which attempt to show a relationship between a mother's health and the well-being of her child. The effects of smoking are a particularly important issue as it is seen as a preventable variable in the birth equation.[2]

The average gestational period for a baby is 40 weeks. A baby is considered preterm when it is born before 37 weeks, with some babies staying in utero for up to 42 weeks. At 28 weeks, the fetus weights in at roughly 4-5 lbs and 40 cm long. At 32 weeks, the fetus is now about 5-5.5 lbs and 45 cm in length. In the final weeks babies gain 0.2 lbs per week. Average newborns range from 5.5 to 8.8 lbs and are usually 45 to 55 cm in length. Babies that weigh less than 5.5 lbs at birth term are considered small.[2]

The common hypothesis which links smoking to birth weight states that the carbon monoxide in cigarette smoke reduces oxygen supplied to the fetus. The physiological effects of decreased oxygen supply are not fully understood at this time, but it is believed that a steady supply of oxygen is critical for a developing fetus. One hypothesis is that to compensate for the lack of oxygen, the placenta increases in both surface area and number of blood vessels. This may lead to an "abruptia placenta," a condition where the placenta breaks away from the uterine wall. The results of such a break can be a preterm delivery or even fetal death.[2]

4 Investigation

Our investigation consists of 5 parts. The first involves analyzing the distributions and means of the weights of babies born to smokers and non-smokers. Next, we consider graphical methods of comparing the two. After that, we will consider the incidence of low-weight babies for smokers and non-smokers, and then discuss the implications of these findings. Finally, we will determine if smoking affects the baby's gestational age.

4.1 Numerical Analysis of Distributions

First considering the distribution of weights of children of smokers, we find that the sample mean is 114.1 ounces, and the sample standard deviation is 18.1 ounces. For the babies of non-smokers, the sample mean is 123 ounces, and the sample standard deviation is 17.4 ounces. Furthermore, we can create 2 95% confidence intervals for the mean: one simply using the typical method with our sample mean and standard error, the other using bootstrap (the reasoning for both will be explained in the theory section). The confidence intervals are displayed in the table below.

Category	T-interval	Bootstrap
Non-smoker	(121.79, 124.30)	(121.78, 124.13)
Smoker	(112.49, 115.73)	(121.79, 124.30)

Figure 1: Confidence interval for mean weight of baby for smokers and non-smokers using T-interval and bootstrap percentile interval.

Looking at percentiles, we find the median weight for the smoking population to be 115 ounces, and for the non-smoking population it is 123 ounces. The proximity of the median for each sample to their respective means would indicate that both distributions are symmetrical, or at least fairly close to it.

We can confirm this by calculating the skewness of our distributions, and furthermore, if we compute the kurtosis we can compare it to a normal distribution. The smoking sample has a skewness of -.034 and a kurtosis of 2.988. This is fairly close to what we would expect from a normal distribution, which has a skewness of 0 and a kurtosis of 3. On the other hand, the non-smoking sample has a skewness of -0.187, and a kurtosis of 4.03706, which indicates it may deviate from a normal distribution. The data appears to be slightly skewed left and somewhat heavy tailed.

4.2 Graphical Analysis of Distribution

We can see from the histograms that both distributions are unimodal and fairly symmetric. From Figure 4, we can easily see that smoker's graph is more right centered than nonsmoker' graph. Thus this confirms, to an extent, the findings of the numerical analyses.

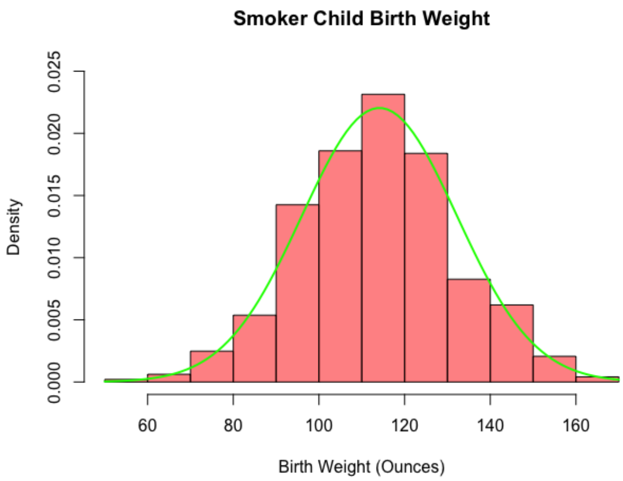

Figure 2: Histogram of birth weights of children born to smokers

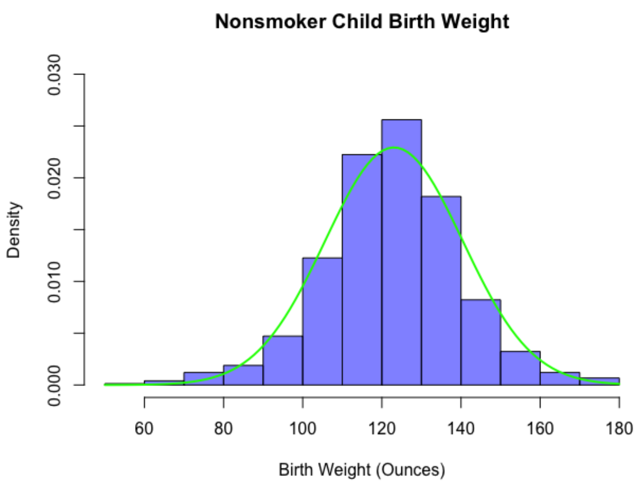

Figure 3: Histogram of birth weights of children born to non-smokers

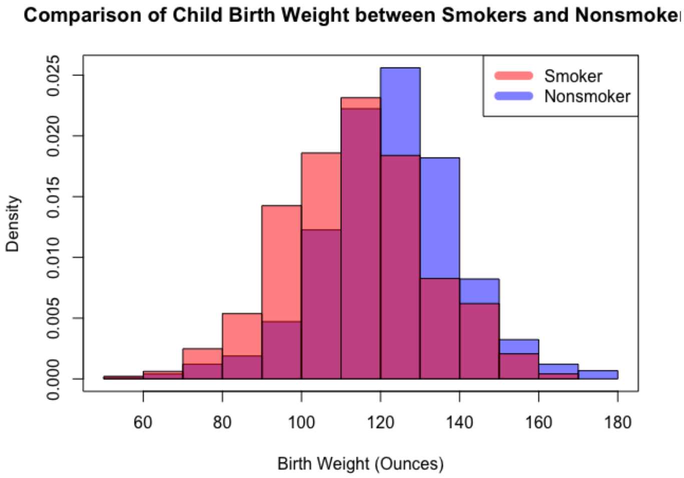

Figure 4: Comparing smoker and nonsmoker birth weight distributions

The boxplot further affirms the findings of the numerical analysis in that it shows distinctly the difference in median, and due to the relative symmetry of the samples, a difference in mean.

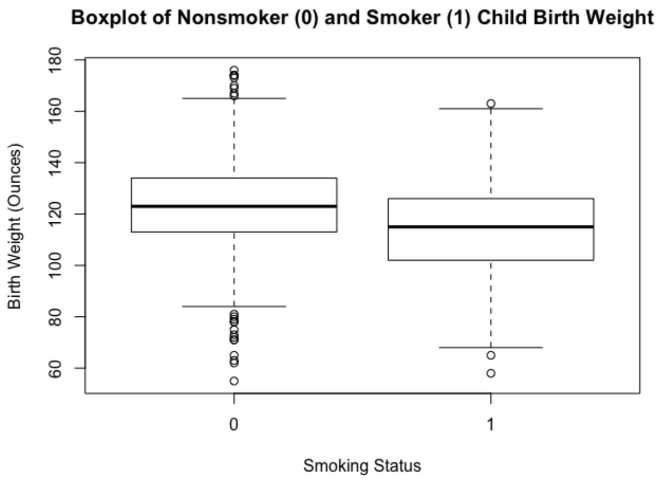

Figure 5: Boxplot of Weight

4.3 Summary of Incidence

Category	Low Weight	Healthy Weight
Non-smoker	22	720
Smoker	36	448

Figure 6: Tabulation of low weight (< 88 ounces) and healthy weight babies for smokers and non-smokers.

We consider babies weighing less than 5 lbs, 8 ounces (88 ounces) to be "low weight", as used by many hospitals and papers. Referring to the counts in Figure 6, we observe that babies of smokers have a low weight incidence of 0.07438, while babies of non-smokers have an incidence 0.02965, which upon first glance seems to be quite significant. Testing for the equality of the two proportions, with the alternative being that the proportion of low weight babies is higher in smokers, we get a p-value of .0002, which indicates that there is significant evidence that the proportion is in fact greater in smokers than in non-smokers.

Having come to this conclusion, it is natural to ask how much the threshold at which we classify babies as low weight would affect our incidence rates. Obviously, proportions will increase as the threshold increases, and decrease as the threshold decreases; what we are truly interested in is how much the proportions change relative to one another. Thus, consider Figure 7, which plots the threshold for each category, smoker and non-smoker, as the threshold moves from 80 to 96 in increments of 2. Looking at this graph, there are two important things to notice - first, that there is a sharp increase in proportion of low weight babies for smokers when going from a threshold of 86 ounces to 88 ounces, and second, that as the threshold increases beyond 88 ounces, the gap in the incidences only increases.

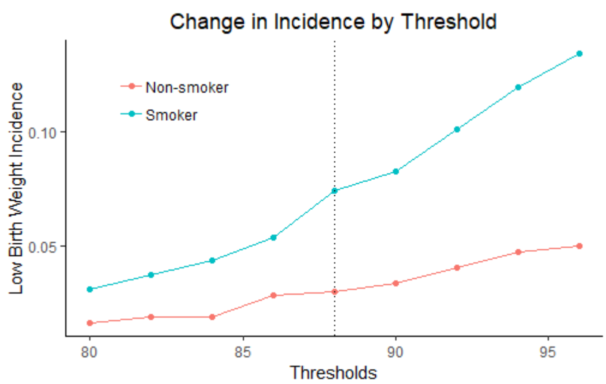

Figure 7: Plot of incidence as threshold changes from 80 to 96. The dotted line represents the true threshold of 88 ounces.

Regarding the first observation, we see that while the incidence for smokers jumps quite distinctly when the threshold goes from 86 to 88 ounces, the incidence for non-smokers increases only slightly. Thus it seems that if we decreased the threshold just 2 ounces (56.7 grams), we might see a slightly different picture. That being said, performing a one-sided test for equality of proportions, we get a p-value of only 0.01, indicating we would still say there is significant evidence that smokers tend to have low weight babies more often than non-smokers.

Looking at the second point, we consider the incidence as the threshold moves past 88 and notice that the incidence of low weight babies increases much more quickly for smokers than it does for non-smokers. This further indicates that the distribution of weights for smokers is shifted slightly left to that of non-smokers, as there are a much greater proportion of babies considered low weight at these thresholds for smokers than for non-smokers. This reinforces the claim that smoking does have an negative effect on birth weight.

4.4 Synthesizing the Findings

It is clear that at this point our sample shows a distinct difference in the distribution of weights of babies of smokers versus those of nonsmokers. The average birth weight of the child of a smoker is significantly less than that of a non-smoker. Furthermore, we showed that it is more likely for babies of non-smokers to be born under a threshold considered to be low weight (88 ounces). Then the most natural thing to explore next is whether or not this difference actually matters. That is, does being a lower weight, or specifically under the threshold of low birth weight, actually cause an infant any harm? The answer to this question, unsurprisingly, is an unequivocal yes. It is well documented that being born with a low birth weight, or preterm is unhealthy. In a study published by the American Academy of Pediatrics, it was found that infants born late-preterm (that is, between 35-37 weeks) have a 22% chance of dying within 28 days of birth, as opposed to 3% for babies born at birth[6]. While this classification of preterm is based on time of birth, rather than weight, an epidemiological study published in the Reproductive Health Journal states that that birth weight and gestational age are closely linked, although birth weight is occasionally more prone to misclassification of preterm births to the possible range of healthy weights[1]. Thus, taking care not to be too overzealous in our connections, we may link some of the effects of preterm birth with those of low birth weight. Furthermore, preterm birth may have long term effects such as increased chance of cerebral palsy, blindness, deafness, and even cognitive outcomes such as increased chance of having low IQ[4].

Thus, from our research and analysis of our data, it seems that smoking does affect birth weight, and in fact, this decrease in birth weight can have negative repercussions for the child's health in both the short and long term.

4.5 Effect of Smoking on Gestational Age

Finally, we will examine the relationship between smoking and gestation period. From what we have seen in our review of literature, we expect that the children of smokers should have smaller gestational ages than the children of non-smokers. We would like to verify this. The sample mean for gestation period in those who smoked is 278 days, with a sample standard deviation of 15.07 days. The mean gestation period for mothers who did not smoke is 280.2 days with a sample standard deviation of 16.63 days. Once again, we can create 2 95% confidence intervals for the mean. The confidence intervals are displayed below.

Category	T-interval	Bootstrap
Non-smoker	(278.98, 281.39)	(278.90, 281.37)
Smoker	(276.63, 279.33)	(276.60, 279.46)

Figure 8: Confidence interval for mean gestation period for babies of smokers and non-smokers using T-interval and bootstrap percentile interval.

Next, we will examine the percentiles for smokers and nonsmokers. The median gestation period for smokers is 279 days and for nonsmokers it is 281 days. These are very close to the mean of the sample, suggesting the distributions are symmetric.

We will now examine the normality of our data by looking at its skewness and kurtosis. We will compare the skewness and kurtosis of our sample data with the expected skewness of 0 and kurtosis of 3 that is found in the normal distribution. Gestation period from the smoking sample has a skewness of -0.22 and a kurtosis of 5.05. This suggests that the data is slightly left skewed with a somewhat heavy tails. The nonsmoking sample had a skewness of -1.08 and a kurtosis of 11.76. This suggests that the data is left skewed and heavy tailed. Looking at the graphics below, we can affirm that this is the case. The quantile-quantile plots are very tail heavy for both smokers and non-smokers, though the skewness is not so apparent to the eye.

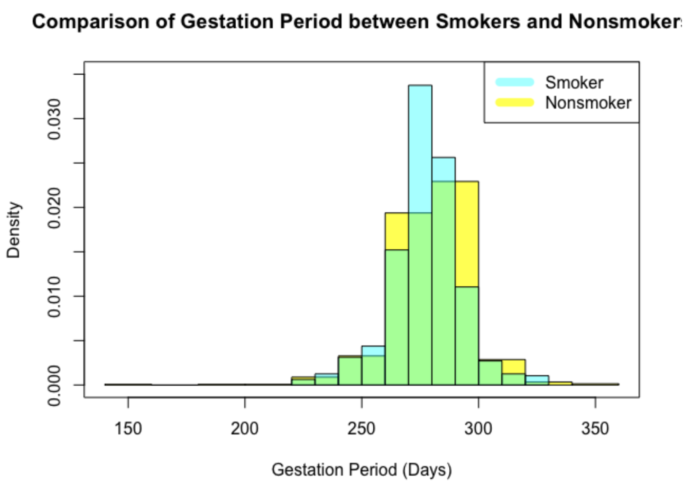

Figure 9: Comparing Gestation Period for Smokers and Nonsmokers

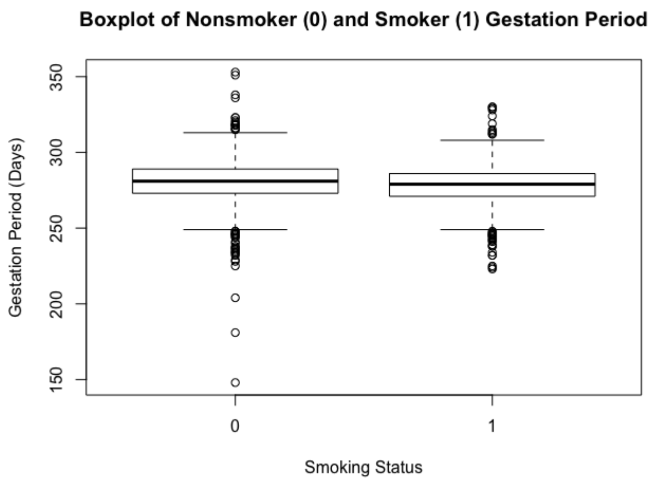

Figure 10: Gestation Boxplot

The boxplot, Figure 10, shows a similarity in distribution - the medians are not very far apart, and neither are the quartiles. Below, the Q-Q plots show the how heavy tailed the data is. It seems fairly obvious that these are not normally distributed.

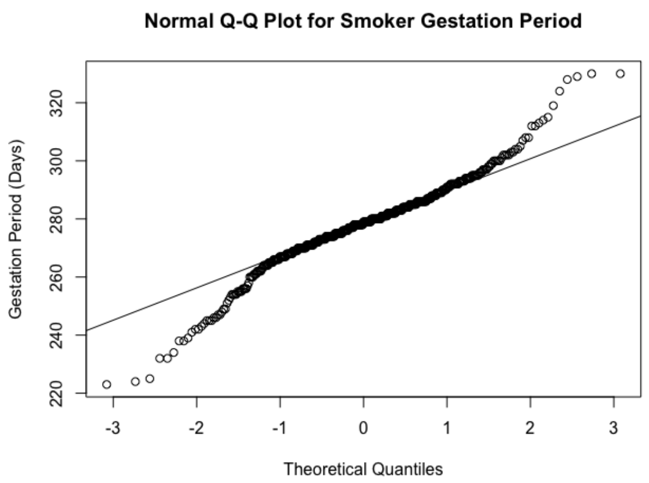

Figure 11: Normal Q-Q Plot for Gestation Period in Smokers

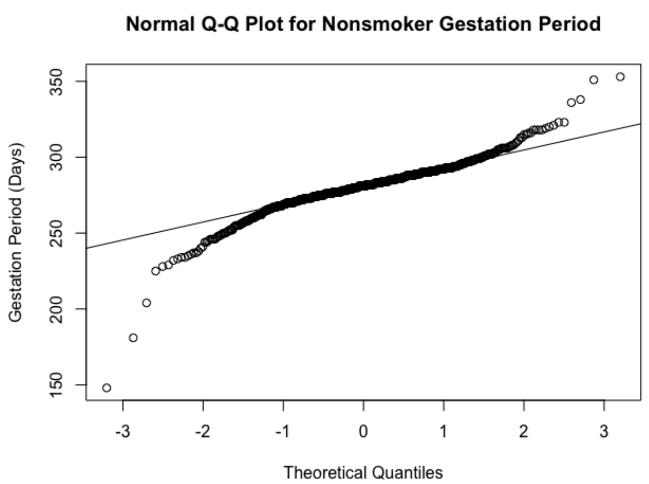

Figure 12: Normal Q-Q Plot for Gestation Period in Nonsmokers

Although previous studies found that smoking had a large effect on gestation period, we were not able to replicate these results with our dataset. The mean and median gestation periods for smokers and non-smokers were extremely close to one another. In fact, the mean gestation period for nonsmokers from our data was actually lower than the mean for smokers. This may be a result of a few outliers found in the nonsmokers data, where the gestation period was below 200 days. In addition, there may have been other potential confounding variables we did not take into account when looking at this data, such as social class or a mothers overall health. Our results may have also been affected by our dataset's specificity, which reduced the scope and generalizability of our data.

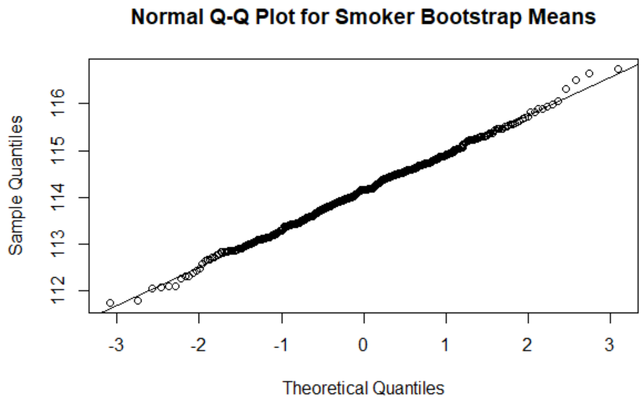

Figure 13: Normal Q-Q plot for the bootstrapped means of birth weights of children of smokers

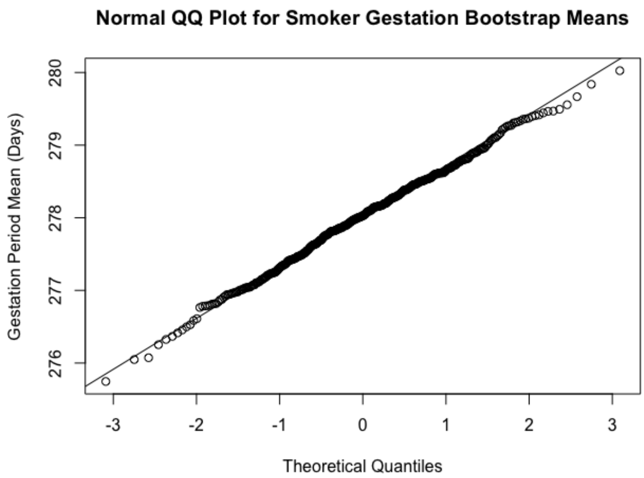

Figure 14: Normal Q-Q Plot for the Bootstrapped Gestation Means of Smokers

5 Theory

The theory will be split up into similar sections as the investigation, and the theory used in each part of the investigation will then be discussed.

5.1 Numerical Analysis

We estimate the mean of the true distribution for each category by the sample mean, which is known to be an unbiased estimator for mean when data is i.i.d. For similar reasons, we use the sample standard deviation to approximate the true standard deviation. There were then two types of confidence intervals used for the sample mean at significance levels of 95%. The first was the T-interval, which is simply $\bar{x} \pm t_{n-1}^{.975}(\frac{\sigma}{\sqrt{n}})$. The accuracy of this interval, or at least the optimality of its probability, depends on the normality of $\bar{x}$. Thus, the following procedure was completed for each sample (smokers and non-smokers). First, 500 bootstrap samples (i.e. samples with replacement) were taken from the original sample. These bootstrap samples were the same size as the original sample. Next, the mean for each sample was computed. To ensure normality, a two-sided Kolmogorov-Smirnov test was performed at the 0.05 level on the collection of bootstrapped sample means. Both the smoker and non-smoker bootstrap sample for means appeared to be normally distributed, and thus we deemed the t-distribution based confidence interval. Examples of the Q-Q plots which support this decision are shown below (the other two are left out for brevity).

To provide a more conservative interval as well, the bootstrap percentile intervals were also given. The endpoints of the bootstrap percentile interval are simply the 0.025 and 0.975 quantiles of the bootstrapped sample means. When analyzing the effect of smoking on gestational age, the first confidence interval was not given because the samples quite clearly did not follow a normal distribution.

Median, skewness and kurtosis were also considered. In a symmetrical distribution, the median and mean take the same value, which led to such a conclusion being made about the two samples. Skewness and kurtosis are the third and fourth moments of a random variable, respectively. Skewness gives a value, unsurprisingly, for the skew of the data - that is, whether it has a longer tail on either side. Symmetric distributions, such as the normal distribution, have 0 skewness. A negative skewness implies a longer tail to the left, whereas a positive skewness implies a longer tail to the right. Kurtosis is a representation of how heavy the tails of the distribution are. More accurately, it is a measure of outliers in the data, and how much they affect its spread. A normal distribution has kurtosis 3.

5.2 Graphical Analysis

Histograms are essentially a way of estimating the density of a function. It is important to choose a bin count that preserves smoothness but also shows any irregularities the sample may contain. Furthermore, when comparing two histograms, one should ensure they share the same axes. Using histograms, one can approximate the median, as well as any modes in the distribution. Boxplots can be used for similar things as histograms (i.e. seeing the distribution of the data). Boxplots show medians and quantiles explicitly, and also display outlier points. Boxplots make it easy to see differences in median and spread between two samples. Finally, we consider quantile-quantile plots. Quantile-quantile plots directly compare the quantiles of either 2 samples, or a sample with a known distribution (e.g. the normal distribution). If the 2 samples come from the same distribution, we expect to see the points land on the line y = x. If there is curvature, a difference in slope, or a difference in intercept, we can conclude that the samples do not follow the same distribution. We follow a similar method when assessing a quantile-quantile plot comparing a sample with a known distribution.

5.3 Incidence Analysis

When analyzing the incidence of low-weight babies in each sample, we essentially consider the samples to be from an i.i.d Bernoulli distribution, where we assign 1 to the unit if the birth weight was $<$ 88 ounces, and 0 otherwise. Then, by the Central Limit Theorem, and more specifically the binomial approximation to the normal distribution, we can use a Z-test of proportions to check whether or not the incidence of low birth weight is the same for both groups. The incidence is just the average of the x_i. Again, though, one must check normality, which we did once again using bootstrap in the same method as the numerical analysis section. We created many bootstrap samples, found the means, and then studied the distribution of those means. Then we checked how the incidence would change as we moved the threshold for low-weight. The important part here was not so much how much each incidence changed as much as it was how much they changed relative to one another. The important point would be to ensure there is statistically significant difference between the incidences for each threshold. It is also important to keep in mind that since these birth weights are considered low, they are already in some way outliers, which means decreasing the threshold would inherently make the proportions closer as we look for more and more low-probability points.

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