An Investigation of Factors Influencing Emergency Healthcare Expenditures

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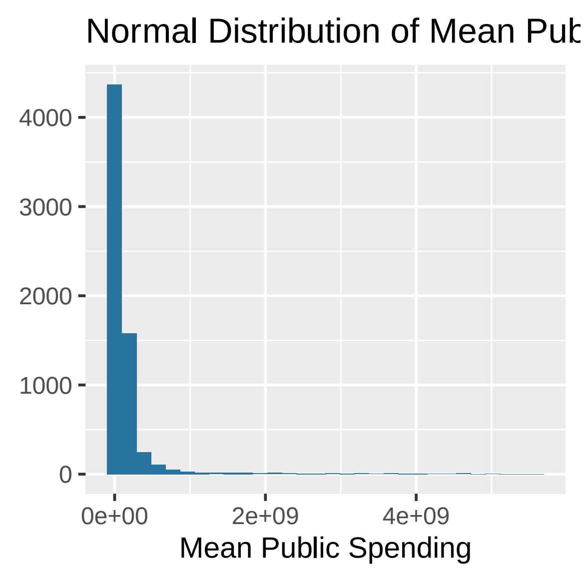
Abstract

Nature of the Data

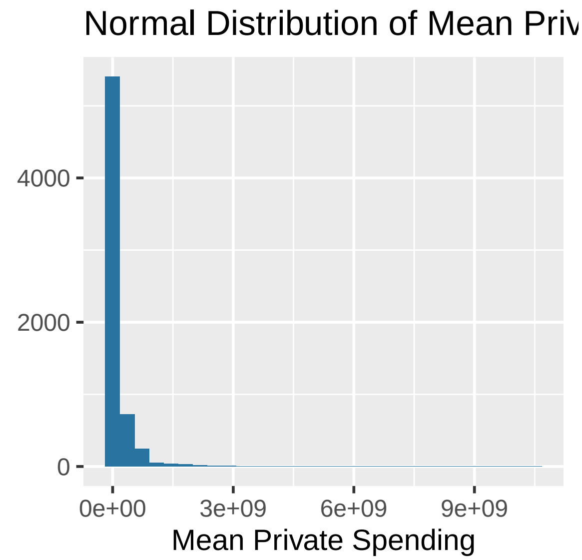
The data includes summary of both male and female spending as "both", so in order to perform an analysis on this data, we decided to exclude the both data points to avoid double counting? It is important to acknowledge that this data only included those who identified as either male or female, so this is not a complete representationof the population.

```
spending_malefemale <- spending %>%
  filter(sex %in% c("Female", "Male"))
```

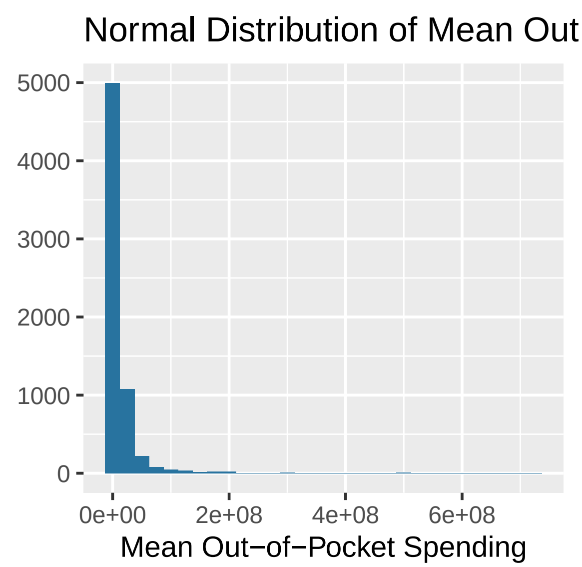
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

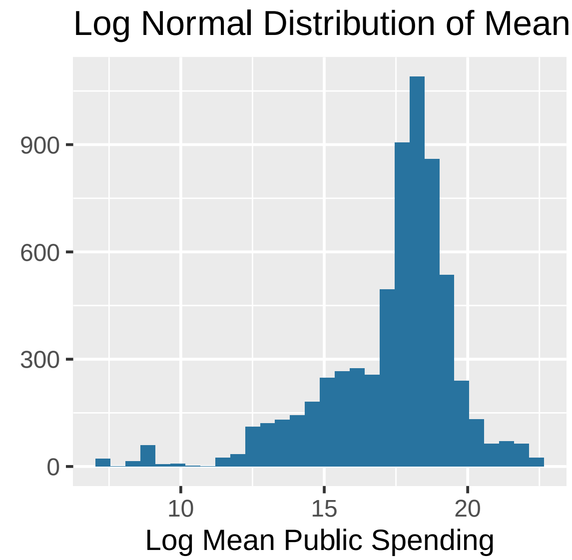


`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

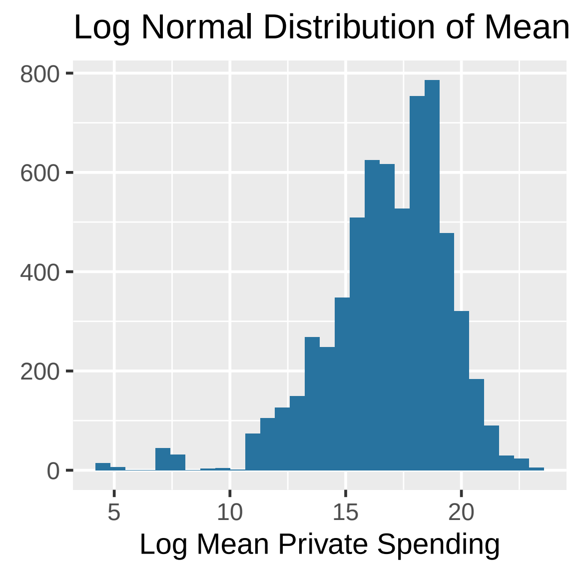


The normal distribution for public spending, private spending, and out-of-pocket pending all show a severe right skew in the data. Therefore, all three variables do not meet the normal distribution assumption needed for many tests, such as ANOVA; however, this can easily be resolved by applying a log transformation to the data to give a fairly normal distribution of the data.

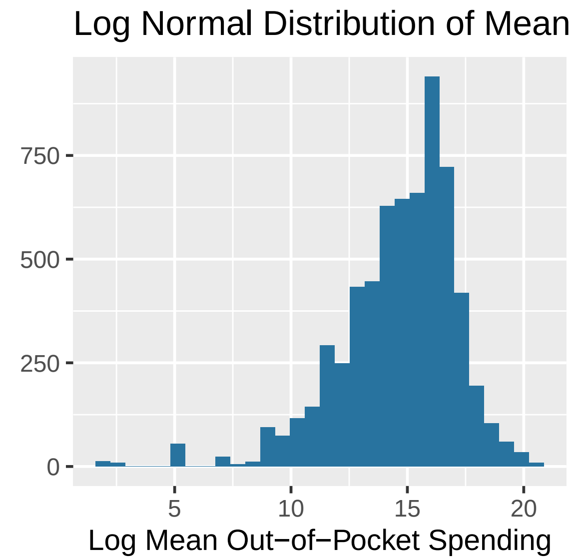
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



These graphs of the log distribution of the various spending means appear to be fairly normal in distribution, which means they meet the requirements to be used in various analyses. In order to convert to log scale, those with mean_all, mean_pub, mean_pri, and mean_oop equal to zero must be excluded.

```
spending_malefemale <- spending_malefemale %>%
  filter(mean_all != 0) %>%
  filter(mean_pub != 0) %>%
  filter(mean_pri != 0) %>%
  filter(mean_oop != 0) %>%
  mutate(lmean_all = log(mean_all)) %>%
  mutate(lmean_pub = log(mean_pub)) %>%
  mutate(lmean_pri = log(mean_pri)) %>%
  mutate(lmean_oop = log(mean_oop))
```

Gender

Our first question in this analysis is if males and females spend a different amount of money on emergency services.

First this t-test looks at overall differences in log mean emergency department spending between males and females

```
  t.test(spending_malefemale$lmean_all~spending_malefemale$sex) %>%
  print()
```

```
##
##  Welch Two Sample t-test
##
## data:  spending_malefemale$lmean_all by spending_malefemale$sex
## t = 1.4247, df = 6219.5, p-value = 0.1543
## alternative hypothesis: true difference in means between group Female and group Male is not equal to
## 95 percent confidence interval:
##  -0.0315862  0.1996079
## sample estimates:
## mean in group Female   mean in group Male
##             18.06275             17.97874
```

This t-test shows that for mean spending of all emergency services payment types, the p value of 0.1543 (95%

CI -0.0315862, 0.1996079) indicates there is not a significant difference between male and female spending.

Next, we perform a t-test on each type of insurance to see if there is a difference in spending between males and females:

```
t.test(spending_malefemale$lmean_pub~spending_malefemale$sex) %>%
  print()
```

```
##
##  Welch Two Sample t-test
##
## data:  spending_malefemale$lmean_pub by spending_malefemale$sex
## t = 1.8142, df = 6201, p-value = 0.0697
## alternative hypothesis: true difference in means between group Female and group Male is not equal to
## 95 percent confidence interval:
##  -0.00833746  0.21532602
## sample estimates:
## mean in group Female   mean in group Male
##             17.40512             17.30162
```

The t-test on emergency services spending for people who have public insurance indicates there is not a significant difference between male and female spending, with p value of 0.0697 (95% CI -0.00833746, 0.21532602).

```
t.test(spending_malefemale$lmean_pri~spending_malefemale$sex) %>%
  print()
```

```
##
##  Welch Two Sample t-test
##
## data:  spending_malefemale$lmean_pri by spending_malefemale$sex
## t = 0.70583, df = 6254.9, p-value = 0.4803
## alternative hypothesis: true difference in means between group Female and group Male is not equal to
## 95 percent confidence interval:
##  -0.08283085  0.17603825
## sample estimates:
## mean in group Female   mean in group Male
##             16.82891             16.78231
```

The t-test on emergency services spending for people who have private insurance indicates there is not a significant difference between male and female spending, with p value of 0.4803 (95% CI -0.08283085, 0.17603825).

```
t.test(spending_malefemale$lmean_oop~spending_malefemale$sex) %>%
  print()
```

```
##
##  Welch Two Sample t-test
##
## data:  spending_malefemale$lmean_oop by spending_malefemale$sex
## t = 0.9799, df = 6230.6, p-value = 0.3272
## alternative hypothesis: true difference in means between group Female and group Male is not equal to
## 95 percent confidence interval:
##  -0.0615859  0.1846904
## sample estimates:
## mean in group Female   mean in group Male
##             14.66032             14.59877
```

The t-test on emergency services spending for people who pay out of pocket indicates there is not a significant difference between male and female spending, with p value of 0.3272 (95% CI -0.0615859, 0.1846904).

The t-tests for each type of insurance indicate that there is not enough evidence to reject the null hypothesis that emergency department spending is the same for males and females who have public insurance, private insurance, or pay out of pocket, leading us to the conclusion that gender does not influence emergency spending in the forms of payment studied here.

Disease category and Emergency Spending

In order to determine emergency department spending based on disease type, an ANOVA test is performed due to the data for spending on the log scale being normally distributed, relatively similar variance, and independent.

The null hypothesis for this ANOVA test is that the overall mean of spending are the same for each disease category

```
summary(aov(lmean_all~agg_cause,data=spending_malefemale))
```

```
##                Df Sum Sq Mean Sq F value Pr(>F)
## agg_cause      14  19152  1368.0   521.9 <2e-16 ***
## Residuals    6365  16685     2.6
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Based on the p-value here of <2e-16, these data or more extreme data it is highly unlikely the null hypothesis is true. Therefore, we perform step-down tests using a Holm correction for multiple comparisons.

```
diseasepair <- pairwise.t.test(spending_malefemale$lmean_all,    spending_malefemale$agg_cause, p.adj =
sigpairs <- broom::tidy(diseasepair) %>%
  filter(p.value<0.05) %>%
  arrange(group1,group2)
nrow(sigpairs)
```

```
## [1] 92
```

The step-down t tests indicate 92 disease category pairs are different out of 105, indicating most disease categories do differ in the amount of government spending by the emergency department. !!not sure how to interpet anova i dont think this is right

```
meanpubdiseasecatfit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(mean_pub ~ agg_cause, data = spending_malefemale)
  tidy(meanpubdiseasecatfit)
```

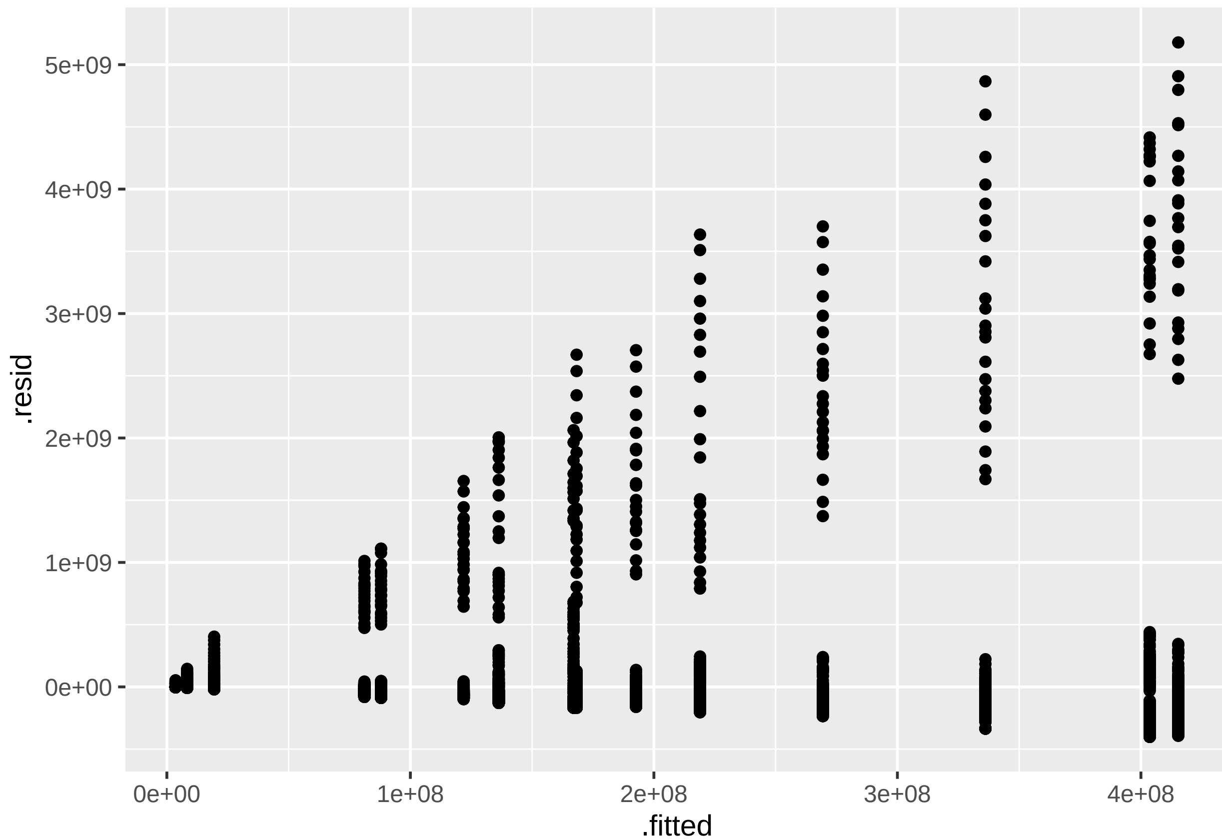
```
## # A tibble: 15 x 5
##    term                                    estimate std.error statistic  p.value
##    <chr>                                      <dbl>     <dbl>     <dbl>    <dbl>
##  1 (Intercept)                               8.80e7 22716720.     3.87  1.09e- 4
##  2 agg_causeCancers                         -7.96e7 32126294.    -2.48  1.32e- 2
##  3 agg_causeCardiovascular diseases          3.16e8 32126294.     9.83  1.27e-22
##  4 agg_causeChronic respiratory diseases     1.05e8 32546263.     3.22  1.30e- 3
##  5 agg_causeCommunicable and nutrition d~    1.81e8 32126294.     5.65  1.70e- 8
##  6 agg_causeDiabetes and kidney diseases    -6.83e6 32126294.    -0.212 8.32e- 1
##  7 agg_causeDigestive diseases               2.48e8 32126294.     7.73  1.29e-14
##  8 agg_causeEndocrine disorders             -6.85e7 32126294.    -2.13  3.29e- 2
##  9 agg_causeInjuries                         3.27e8 32126294.    10.2   3.36e-24
## 10 agg_causeMaternal and neonatal condit~    7.91e7 38135560.     2.07  3.82e- 2
```

```
## 11 agg_causeMusculoskeletal conditions        8.03e7 32126294.     2.50  1.25e- 2
## 12 agg_causeNeurological disorders            4.83e7 32126294.     1.50  1.33e- 1
## 13 agg_causeOther non-communicable disea~     1.31e8 32126294.     4.08  4.61e- 5
## 14 agg_causePrevention and coordination      -8.44e7 32126294.    -2.63  8.64e- 3
## 15 agg_causeSkin and other sense organ d~     3.39e7 32126294.     1.06  2.91e- 1
```

```
augmentaggcausefit <- augment(meanpubdiseasecatfit$fit)
```

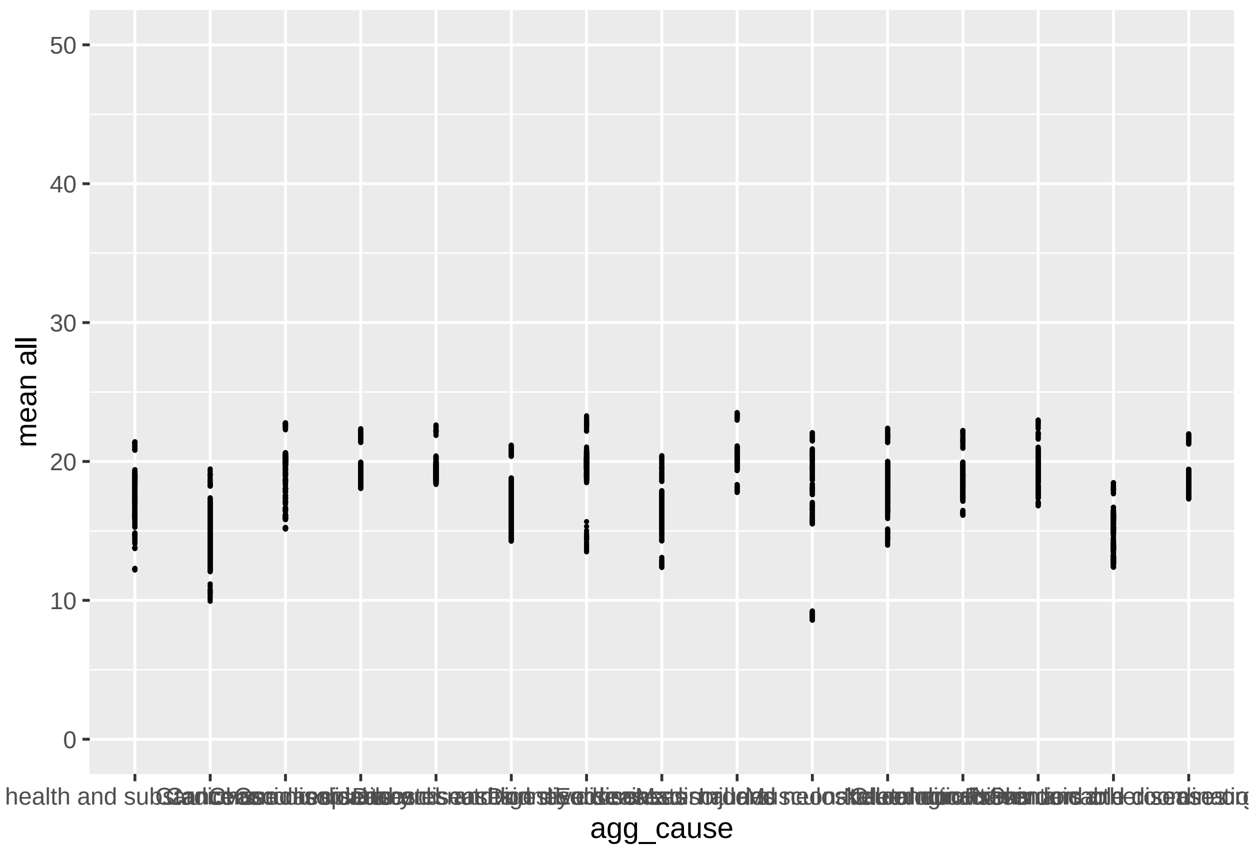
!!this is weird, we need to discuss

```
augmentaggcausefit %>%
  ggplot(aes(x = .fitted,
             y = .resid)) +
  geom_point()
```




```
ggplot(data = spending_malefemale, mapping = aes(x = agg_cause,
                                                 y = lmean_all)) +
  geom_point(size = 0.25) +
  geom_line(data = augmentaggcausefit, mapping = aes(x = agg_cause, y = .fitted)) +
  scale_y_continuous(name="mean all", limits=c(0, 50))
```

```
## Warning: Removed 6380 row(s) containing missing values (geom_path).
```



Age

!! had to take out the observations with "All Ages" because I think it will just mess up the pairs but let me know what you think or whether you think there's anything we can do with that group

```
spending_noall <- spending_malefemale %>%
  filter(age_group_name != "All Ages")
```

We wonder whether there is a correlation between government healthcare expenditures in the emergency department and age. The age variable is categorical, split into 19 groups that generally include 5 years each, apart from the first (<1 year) and last (85 plus) groups.

To address this question, we began by using an overall test with ANOVA.

Below is an overall test of the null hypothesis that all of the means for age groups across the years are equal, as opposed to the alternative that at least one mean is different.

```
summary(aov(mean_all~age_group_name,data = spending_noall))
```

```
##                   Df    Sum Sq   Mean Sq F value Pr(>F)
## age_group_name    18 2.843e+19 1.579e+18   29.45 <2e-16 ***
## Residuals       6031 3.235e+20 5.364e+16
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

In this F-test (ndf = 18, ddf = 6229), a significant difference among age groups was identified. Our p-value tells us that this data (or data more extreme) would be very unlikely if the null hypothesis were true because it shows statistical significance at an alpha well below 0.05. Therefore, we reject the null hypothesis that the mean expenditures for all age groups are equal.

To see which specific means may be different from one another, we used planned step-down tests with a Holm correction to minimize Type I errors.

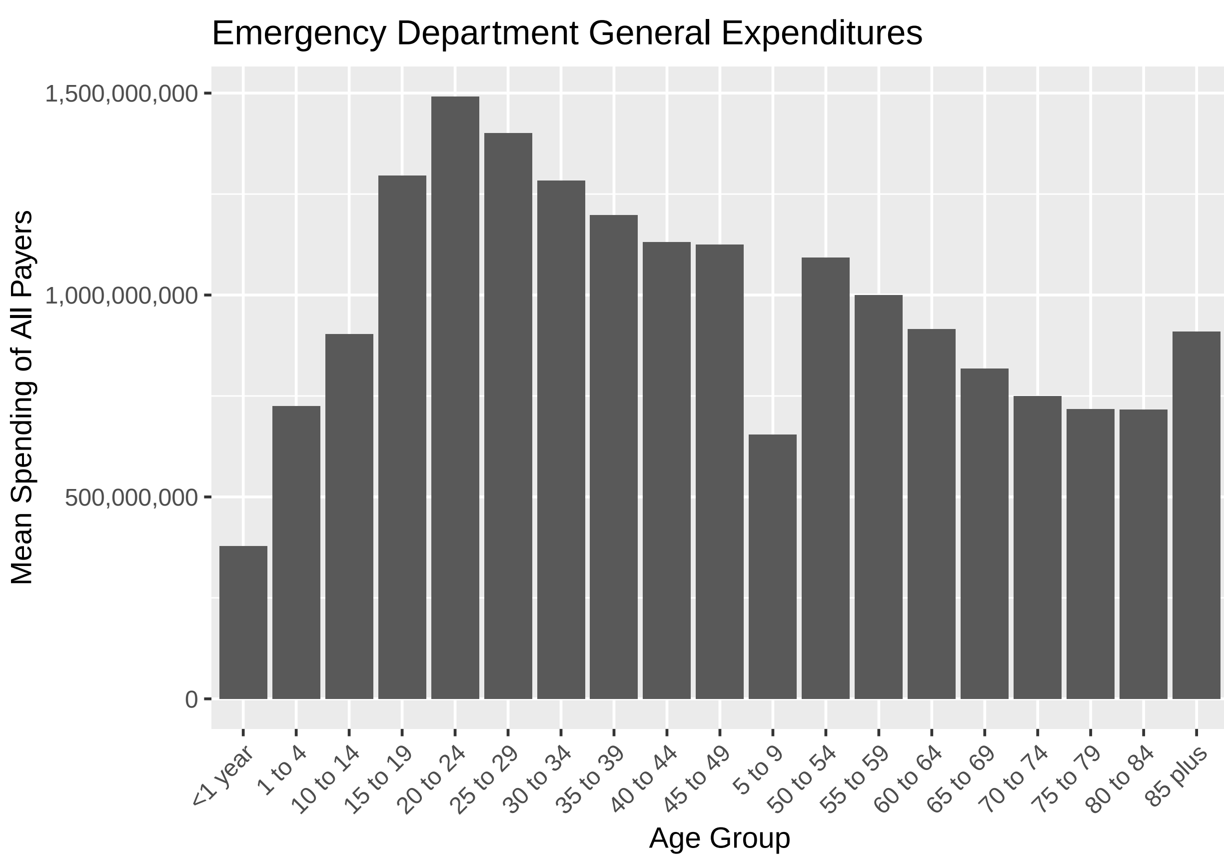
```
agepair <- pairwise.t.test(spending_noall$mean_all, spending_noall$age_group_name, p.adj = "holm")
sigagepairs <- broom::tidy(agepair) %>%
  filter(p.value<0.05) %>%
  arrange(group1,group2)
nrow(sigagepairs)
```

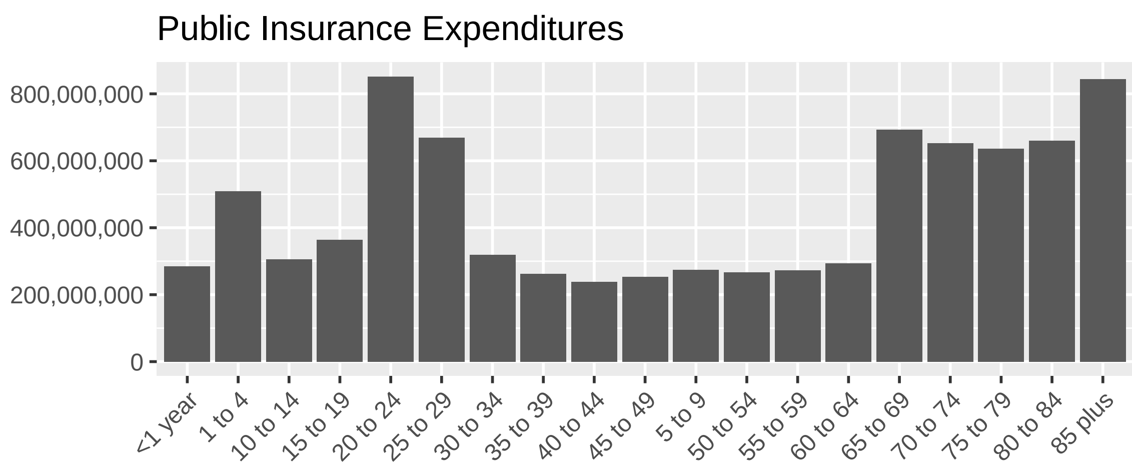
```
## [1] 98
```

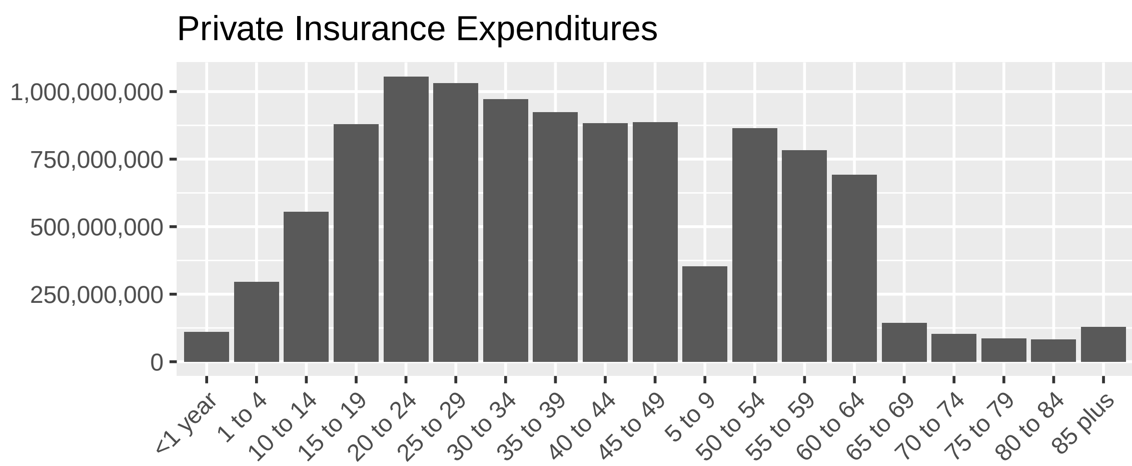
The pairwise t-tests used for our ANOVA step-down tests suggest that there are 97 different age pairs out of the 171 possible combinations. This tells us that more age pairs are different than are similar and that therefore the majority of age group pairs differ in terms of mean expenditures.

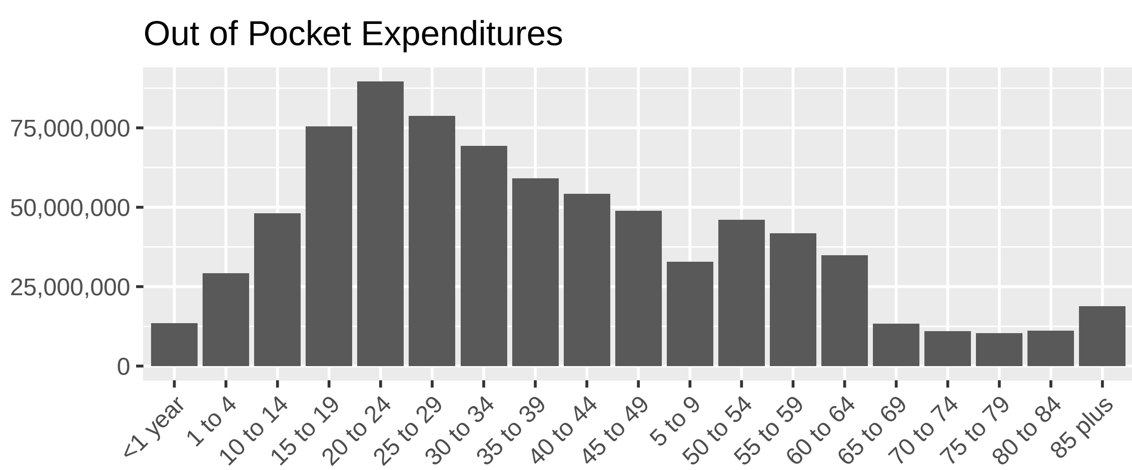
```
  # select the variables want, including the mean for the groups, age_group_name
  # pivot_longer -> cols, names_to = "whateveryouwant", values_to = "customname %>%
  # ggplot(aes(x = age_group_name, y = custommame, color = whateveryouwant))

ggplot(data = spending_noall, aes(x = age_group_name, y = mean_all)) +
  geom_bar(position = "dodge", stat = "identity") +
  theme(axis.text.x = element_text(angle = 45,hjust = 1)) +
  scale_y_continuous(labels = scales::comma) +
  labs(
    x = "Age Group",
    y = "Mean Spending of All Payers",
    title = "Emergency Department General Expenditures"
      )
```









Gender and Age Interaction

```
mainefpub_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(lmean_pub ~ sex + age_group_id, data = spending_malefemale)
tidy(mainefpub_fit)
```

```
## # A tibble: 3 x 5
##   term          estimate std.error statistic  p.value
##   <chr>            <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)  17.3      0.0445      390.   0
## 2 sexMale      -0.104    0.0574       -1.80 0.0712
## 3 age_group_id  0.00328  0.000887      3.70 0.000216
```

```
glance(mainefpub_fit)$adj.r.squared
```

```
## [1] 0.002338971
```

```
interpub_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(lmean_pub ~ sex + age_group_id + sex*age_group_id, data = spending_malefemale)
tidy(interpub_fit)
```

```
## # A tibble: 4 x 5
##   term                 estimate std.error statistic p.value
##   <chr>                   <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)          17.3       0.0483    359.    0
## 2 sexMale              -0.0803    0.0694     -1.16  0.247
## 3 age_group_id          0.00379   0.00123     3.08  0.00211
## 4 sexMale:age_group_id -0.00106   0.00177    -0.595 0.552
```

```
glance(interpub_fit)$adj.r.squared
```

```
## [1] 0.002237904
```

```
mainefpri_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(lmean_pri ~ sex + age_group_id, data = spending_malefemale)
tidy(mainefpri_fit)
```

```
## # A tibble: 3 x 5
##   term          estimate std.error statistic  p.value
##   <chr>            <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)   17.1      0.0508    337.     0
## 2 sexMale       -0.0463   0.0656      -0.707 4.80e- 1
## 3 age_group_id  -0.0132   0.00101    -13.0   3.18e-38
```

```
glance(mainefpri_fit)$adj.r.squared
```

```
## [1] 0.02563492
```

```
interpri_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(lmean_pri ~ sex + age_group_id + sex*age_group_id, data = spending_malefemale)
tidy(interpri_fit)
```

```
## # A tibble: 4 x 5
##   term                 estimate std.error statistic  p.value
##   <chr>                   <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)          17.1       0.0552   310.      0
## 2 sexMale               0.00254   0.0793     0.0320 9.74e- 1
## 3 age_group_id         -0.0121    0.00141   -8.60   1.02e-17
## 4 sexMale:age_group_id -0.00222   0.00203   -1.10   2.73e- 1
```

```
glance(interpri_fit)$adj.r.squared
```

```
## [1] 0.02566573
```

```
mainefoop_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(lmean_oop ~ sex + age_group_id, data = spending_malefemale)
tidy(mainefoop_fit)
```

```
## # A tibble: 3 x 5
##   term         estimate std.error statistic  p.value
##   <chr>           <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)   14.9     0.0485     308.    0
## 2 sexMale       -0.0613  0.0626      -0.980 3.27e- 1
## 3 age_group_id  -0.0113  0.000967   -11.7   3.10e-31
```

```
glance(mainefoop_fit)$adj.r.squared
```

```
## [1] 0.02080634
```

```
interoop_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(lmean_oop ~ sex + age_group_id + sex*age_group_id, data = spending_malefemale)
tidy(interoop_fit)
```

```
## # A tibble: 4 x 5
##   term                 estimate std.error statistic  p.value
##   <chr>                   <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)          14.9       0.0526    283.    0
## 2 sexMale              -0.0181    0.0757     -0.239 8.11e- 1
## 3 age_group_id         -0.0103    0.00134    -7.70  1.59e-14
## 4 sexMale:age_group_id -0.00197   0.00193    -1.02  3.09e- 1
```

```
glance(interoop_fit)$adj.r.squared
```

```
## [1] 0.02081155
```

In order to test the possibility that there is a joint interaction of gender and age, a main effects and interaction effects linear regression model has been fit to the data. As a whole, it shows that the interaction of gender and age slightly increases the accuracy of the regression for public and private spending as seen by the increased adjusted R^2 value. However, for out-of-pocket spending, it decreases the adjusted R^2 value. Nevertheless, overall, the adjusted R^2 values for all three types of spending are incredibly low, which further point to our conclusion that age may not affect the level of spending from different sources.

Age and Disease Type Interaction

```
agedismainpub_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(lmean_pub ~ agg_cause + age_group_id, data = spending_malefemale)
tidy(agedismainpub_fit)
```

```
## # A tibble: 16 x 5
##    term                                 estimate std.error statistic   p.value
##    <chr>                                   <dbl>     <dbl>     <dbl>     <dbl>
##  1 (Intercept)                          17.1      0.0780     219.    0
##  2 agg_causeCancers                     -2.68     0.109      -24.6   3.75e-128
##  3 agg_causeCardiovascular diseases      1.16     0.109       10.7   1.92e- 26
##  4 agg_causeChronic respiratory diseases  1.27     0.110       11.5   2.51e- 30
##  5 agg_causeCommunicable and nutrition d~  1.59     0.109       14.6   1.68e- 47
```

```
##  6 agg_causeDiabetes and kidney diseases   0.0502   0.109        0.462 6.44e-  1
##  7 agg_causeDigestive diseases             1.64     0.109       15.1   1.30e- 50
##  8 agg_causeEndocrine disorders           -1.27     0.109      -11.7   2.94e- 31
##  9 agg_causeInjuries                       1.97     0.109       18.1   1.68e- 71
## 10 agg_causeMaternal and neonatal condit~ -3.14     0.129      -24.4   1.03e-125
## 11 agg_causeMusculoskeletal conditions     0.806    0.109        7.42  1.32e- 13
## 12 agg_causeNeurological disorders         0.760    0.109        7.00  2.77e- 12
## 13 agg_causeOther non-communicable disea~  1.23     0.109       11.3   1.65e- 29
## 14 agg_causePrevention and coordination   -3.06     0.109      -28.2   3.71e-165
## 15 agg_causeSkin and other sense organ d~  0.863    0.109        7.95  2.22e- 15
## 16 age_group_id                            0.00334  0.000623     5.35  9.00e-  8
```

```
glance(agedismainpub_fit)$adj.r.squared
```

```
## [1] 0.506887
```

```
agedisinterpub_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(lmean_pub ~ agg_cause + age_group_id + agg_cause*age_group_id, data = spending_malefemale)
tidy(agedisinterpub_fit)
```

```
## # A tibble: 30 x 5
##    term                                   estimate std.error statistic   p.value
##    <chr>                                     <dbl>     <dbl>     <dbl>     <dbl>
##  1 (Intercept)                              17.3      0.0907    191.   0
##  2 agg_causeCancers                         -3.14     0.128     -24.5  1.27e-126
##  3 agg_causeCardiovascular diseases          0.630    0.128       4.91 9.52e-  7
##  4 agg_causeChronic respiratory diseases     1.06     0.129       8.22 2.35e- 16
##  5 agg_causeCommunicable and nutrition d~    1.42     0.128      11.0  4.05e- 28
##  6 agg_causeDiabetes and kidney diseases    -0.244    0.128      -1.90 5.70e-  2
##  7 agg_causeDigestive diseases               1.48     0.128      11.6  1.19e- 30
##  8 agg_causeEndocrine disorders             -1.44     0.128     -11.2  6.78e- 29
##  9 agg_causeInjuries                         1.72     0.128      13.4  2.25e- 40
## 10 agg_causeMaternal and neonatal condit~   -2.34     0.154     -15.2  4.33e- 51
## # ... with 20 more rows
```

```
glance(agedisinterpub_fit)$adj.r.squared
```

```
## [1] 0.529351
```

```
agedismainpri_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(lmean_pri ~ agg_cause + age_group_id, data = spending_malefemale)
tidy(agedismainpri_fit)
```

```
## # A tibble: 16 x 5
##    term                                   estimate std.error statistic   p.value
##    <chr>                                     <dbl>     <dbl>     <dbl>     <dbl>
##  1 (Intercept)                             16.4     0.0903      182.   0
##  2 agg_causeCancers                        -2.24    0.126       -17.8  1.48e- 69
##  3 agg_causeCardiovascular diseases         1.62    0.126        12.9  1.75e- 37
##  4 agg_causeChronic respiratory diseases    1.71    0.127        13.4  1.13e- 40
##  5 agg_causeCommunicable and nutrition d~   2.05    0.126        16.3  2.02e- 58
##  6 agg_causeDiabetes and kidney diseases   -0.245   0.126        -1.94 5.19e-  2
##  7 agg_causeDigestive diseases              2.43    0.126        19.3  6.39e- 81
##  8 agg_causeEndocrine disorders            -0.793   0.126        -6.31 2.99e- 10
##  9 agg_causeInjuries                        3.44    0.126        27.3  9.02e-156
```

```
## 10 agg_causeMaternal and neonatal condit~  -3.16    0.149       -21.2  2.27e- 96
## 11 agg_causeMusculoskeletal conditions      1.50    0.126        11.9  2.36e- 32
## 12 agg_causeNeurological disorders          1.32    0.126        10.5  1.29e- 25
## 13 agg_causeOther non-communicable disea~   2.03    0.126        16.2  1.27e- 57
## 14 agg_causePrevention and coordination    -2.64    0.126       -21.0  2.18e- 94
## 15 agg_causeSkin and other sense organ d~   1.41    0.126        11.2  8.06e- 29
## 16 age_group_id                            -0.0131  0.000722    -18.2  4.45e- 72
```

```
glance(agedismainpri_fit)$adj.r.squared
```

```
## [1] 0.5054947
```

```
agedisinterpri_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(lmean_pri ~ agg_cause + age_group_id + agg_cause*age_group_id, data = spending_malefemale)
tidy(agedisinterpri_fit)
```

```
## # A tibble: 30 x 5
##    term                                    estimate std.error statistic  p.value
##    <chr>                                      <dbl>     <dbl>     <dbl>    <dbl>
##  1 (Intercept)                               16.7       0.106    157.   0
##  2 agg_causeCancers                          -2.77      0.151    -18.4  1.21e-73
##  3 agg_causeCardiovascular diseases           1.05      0.151      6.96 3.67e-12
##  4 agg_causeChronic respiratory diseases      1.50      0.152      9.90 6.18e-23
##  5 agg_causeCommunicable and nutrition di~    1.82      0.151     12.1  2.51e-33
##  6 agg_causeDiabetes and kidney diseases     -0.647     0.151     -4.30 1.74e- 5
##  7 agg_causeDigestive diseases                2.31      0.151     15.3  5.24e-52
##  8 agg_causeEndocrine disorders              -1.04      0.151     -6.94 4.46e-12
##  9 agg_causeInjuries                          3.23      0.151     21.4  1.91e-98
## 10 agg_causeMaternal and neonatal conditi~   -2.78      0.181    -15.4  2.21e-52
## # ... with 20 more rows
```

```
glance(agedisinterpri_fit)$adj.r.squared
```

```
## [1] 0.5149051
```

```
agedismainoop_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(lmean_oop ~ agg_cause + age_group_id, data = spending_malefemale)
tidy(agedismainoop_fit)
```

```
## # A tibble: 16 x 5
##    term                                   estimate std.error statistic   p.value
##    <chr>                                     <dbl>     <dbl>     <dbl>     <dbl>
##  1 (Intercept)                              14.7      0.0850     173.   0
##  2 agg_causeCancers                         -2.75     0.118      -23.3  6.48e-115
##  3 agg_causeCardiovascular diseases          0.975    0.118        8.23 2.17e- 16
##  4 agg_causeChronic respiratory diseases     1.11     0.120        9.26 2.68e- 20
##  5 agg_causeCommunicable and nutrition d~    1.67     0.118       14.1  1.02e- 44
##  6 agg_causeDiabetes and kidney diseases    -0.428    0.118       -3.62 3.03e-  4
##  7 agg_causeDigestive diseases               1.83     0.118       15.5  5.56e- 53
##  8 agg_causeEndocrine disorders             -0.917    0.118       -7.75 1.08e- 14
##  9 agg_causeInjuries                         2.65     0.118       22.4  9.40e-107
## 10 agg_causeMaternal and neonatal condit~   -3.52     0.141      -25.1  1.97e-132
## 11 agg_causeMusculoskeletal conditions       0.888    0.118        7.51 6.94e- 14
## 12 agg_causeNeurological disorders           0.736    0.118        6.22 5.30e- 10
## 13 agg_causeOther non-communicable disea~    1.57     0.118       13.3  1.30e- 39
```

```
## 14 agg_causePrevention and coordination    -3.34    0.118       -28.2  1.73e-165
## 15 agg_causeSkin and other sense organ d~   0.841   0.118         7.10 1.37e- 12
## 16 age_group_id                            -0.0112  0.000680    -16.5  3.10e- 60
```

```
glance(agedismainoop_fit)$adj.r.squared
```

```
## [1] 0.5161683
```

```
agedisinteroop_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(lmean_oop ~ agg_cause + age_group_id + agg_cause*age_group_id, data = spending_malefemale)
tidy(agedisinteroop_fit)
```

```
## # A tibble: 30 x 5
##    term                                   estimate std.error statistic   p.value
##    <chr>                                     <dbl>     <dbl>     <dbl>     <dbl>
##  1 (Intercept)                              14.9       0.100    149.   0
##  2 agg_causeCancers                         -3.18      0.142    -22.4  2.10e-107
##  3 agg_causeCardiovascular diseases          0.404     0.142      2.85 4.34e-  3
##  4 agg_causeChronic respiratory diseases     0.893     0.143      6.26 4.13e- 10
##  5 agg_causeCommunicable and nutrition d~    1.50      0.142     10.6  5.92e- 26
##  6 agg_causeDiabetes and kidney diseases    -0.797     0.142     -5.63 1.91e-  8
##  7 agg_causeDigestive diseases               1.68      0.142     11.9  3.63e- 32
##  8 agg_causeEndocrine disorders             -1.14      0.142     -8.08 7.94e- 16
##  9 agg_causeInjuries                         2.39      0.142     16.9  1.79e- 62
## 10 agg_causeMaternal and neonatal condit~   -3.09      0.170    -18.2  7.93e- 72
## # ... with 20 more rows
```

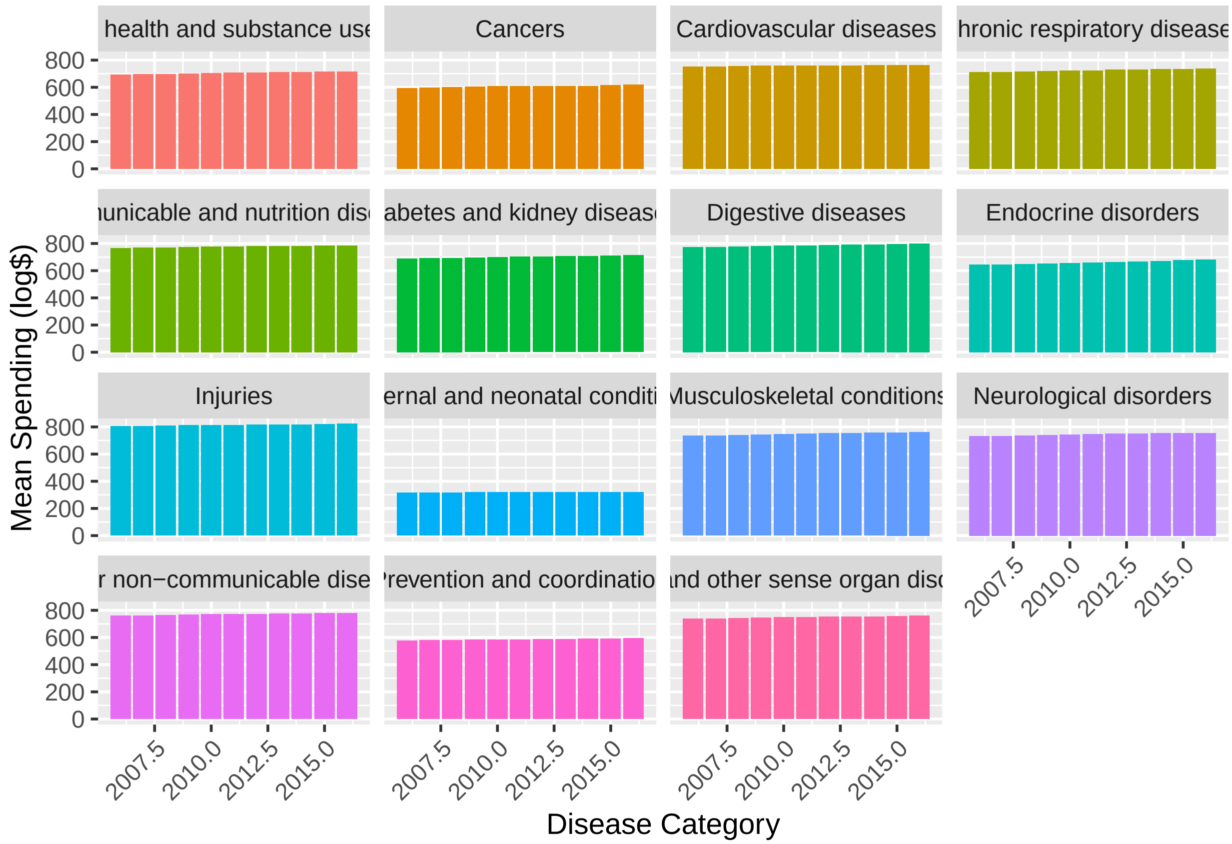
```
glance(agedisinteroop_fit)$adj.r.squared
```

```
## [1] 0.5261024
```

##Spending Over Time

!! I kinda like this but idk if it adds anything but it is fun, need to make the words smaller so you can read it

```
spending_malefemale %>%
  ggplot(aes(x = year_id,
             y = lmean_all,
             fill = agg_cause)) +
  geom_bar(stat = "identity") +
  facet_wrap(~agg_cause) +
  theme(axis.text.x = element_text(angle = 45,hjust = 1), legend.position = "none") +
  labs(x = "Disease Category",
       y = "Mean Spending (log$)")
```



!! can we divide this to have a predictor for each year?

```
spendingovertime_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(lmean_all ~ year_id, data = spending_malefemale)
tidy(spendingovertime_fit)
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic       p.value
##   <chr>          <dbl>     <dbl>     <dbl>         <dbl>
## 1 (Intercept) -92.1      18.8          -4.89 0.00000102
## 2 year_id       0.0548    0.00936      5.85 0.00000000516
```