

An Investigation of Factors Influencing Emergency Healthcare Expenditures

due November 16, 2021 by 11:59 PM

Maggie Lundberg, Riya Mohan, and Izzy Kjaerulff

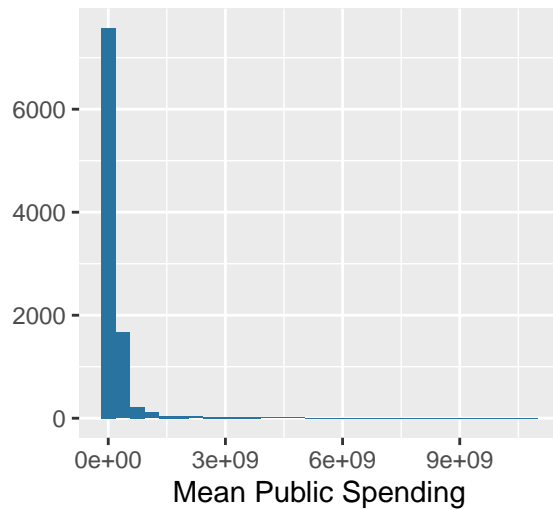
11/16/2021

Abstract

Nature of the Data

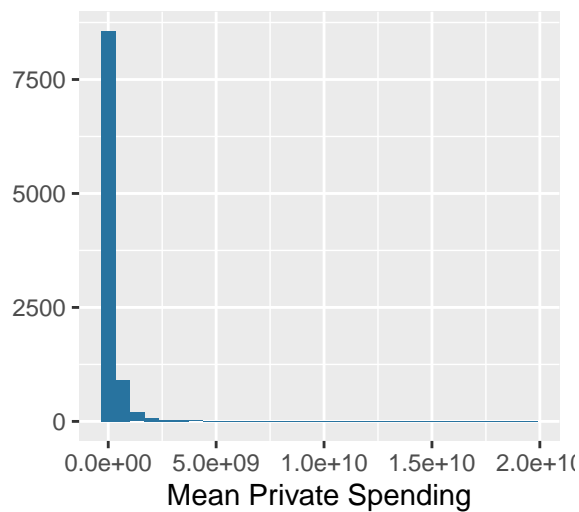
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

Normal Distribution of Mean Pub



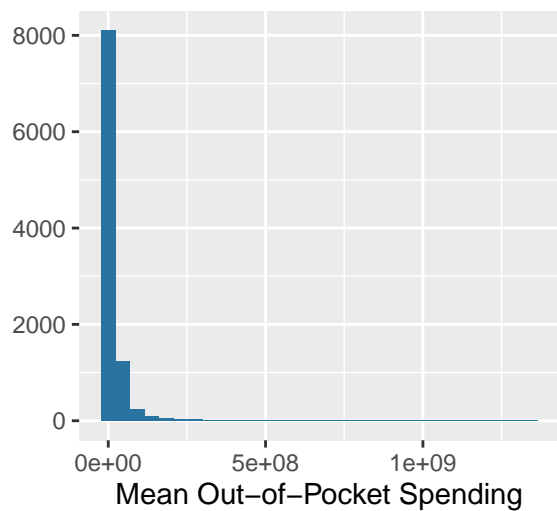
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

Normal Distribution of Mean Priv



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

Normal Distribution of Mean Out

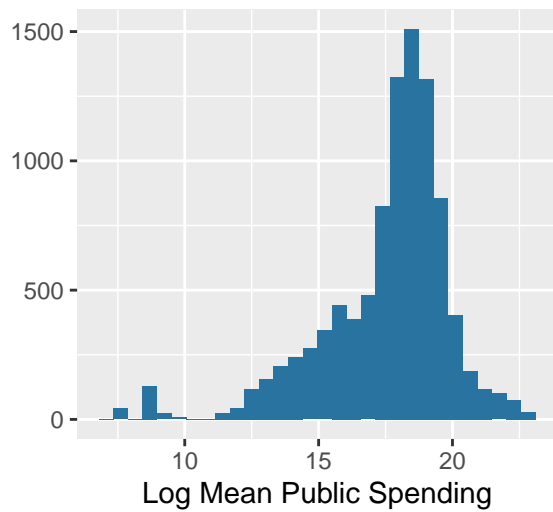


The normal distribution for public spending, private spending, and out-of-pocket spending all show a severe right skew in the data. Therefore, all three variables do not meet the normal distribution assumption needed for many tests, such as ANOVA; however, this can easily be resolved by applying a log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

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

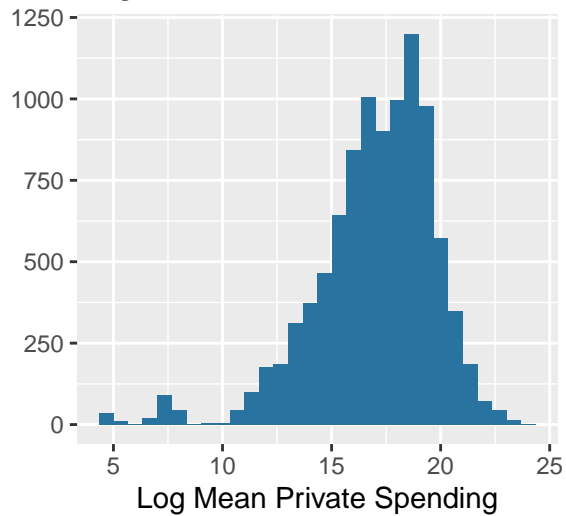
```
## Warning: Removed 198 rows containing non-finite values (stat_bin).
```

Log Normal Distribution of Mean



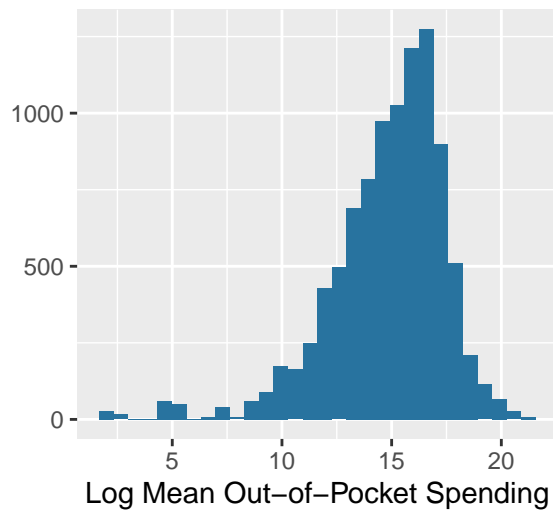
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## Warning: Removed 198 rows containing non-finite values (stat_bin).
```

Log Normal Distribution of Mean



```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## Warning: Removed 198 rows containing non-finite values (stat_bin).
```

Log Normal Distribution of Mean



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.

Gender

Do males and females spend a different amount of money on emergency services?

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

In order to analyze spending, we must convert all mean spending reports to log scale.

```
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))
```

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

```
spending <- spending %>%
  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))
```

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. ANOVA: 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))
```

```
##           Df Sum Sq Mean Sq F value Pr(>F)
## agg_cause   14  30846    2203   744.1 <2e-16 ***
## Residuals 9654  28584         3
## ---
## 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$lmean_all, spending$agg_cause, p.adj = "holm")
sigpairs <- broom::tidy(diseasepair) %>%
  filter(p.value<0.05) %>%
  arrange(group1,group2)
nrow(sigpairs)
```

```
## [1] 95
```

The step-down t tests indicate 95 disease category pairs are different out of 105, indicating most disease categories do differ in the amount of government spending by the emergency department.

ADD treemap if possible

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.

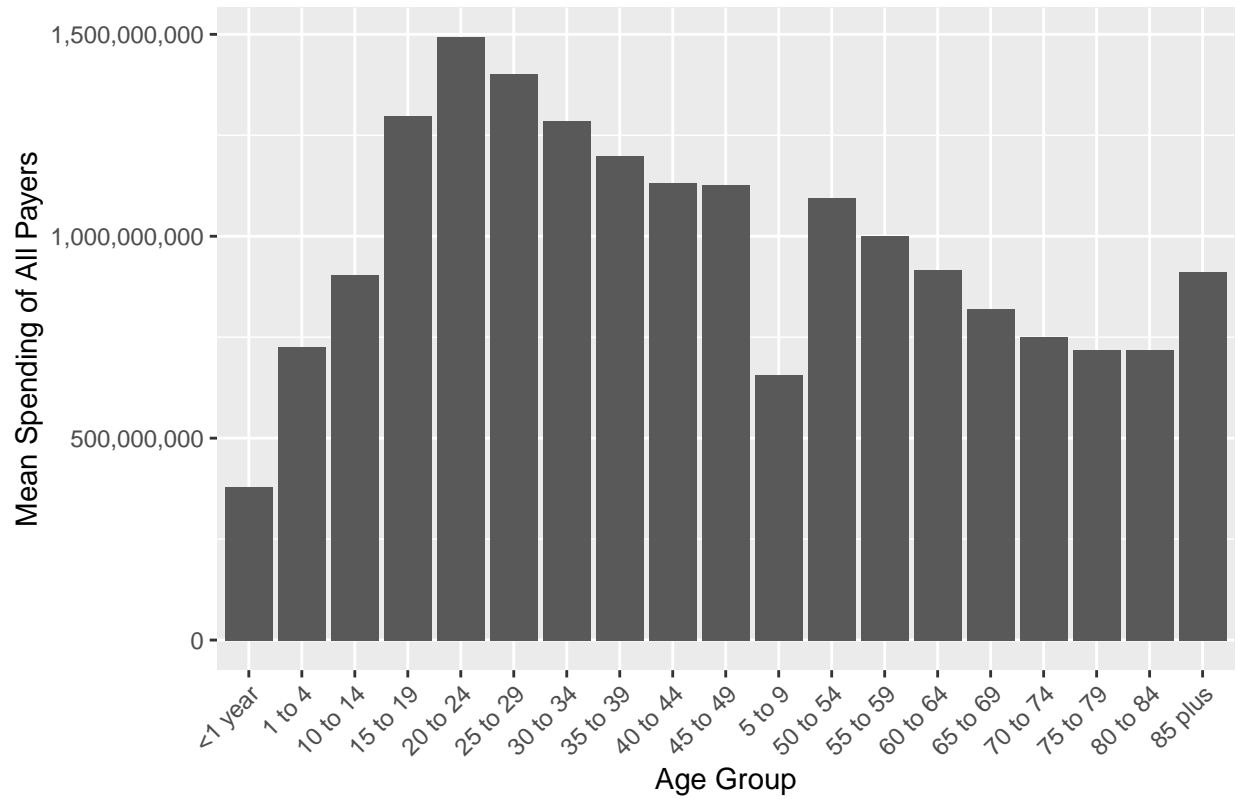
```

# 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 = customname, color = whateveryouwant))

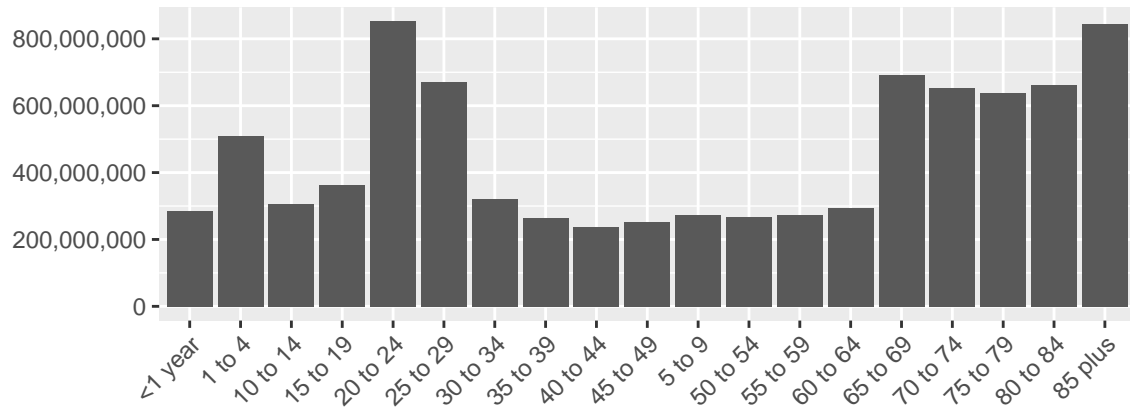
ggplot(data = spending_noall, aes(x = age_group_name, y = mean_all)) +
  geom_bar(position = "dodge", stat = "identity") +
  theme(axis.text.x = element_text(angle = 45,hjust = 1)) +
  scale_y_continuous(labels = scales::comma) +
  labs(
    x = "Age Group",
    y = "Mean Spending of All Payers",
  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

```

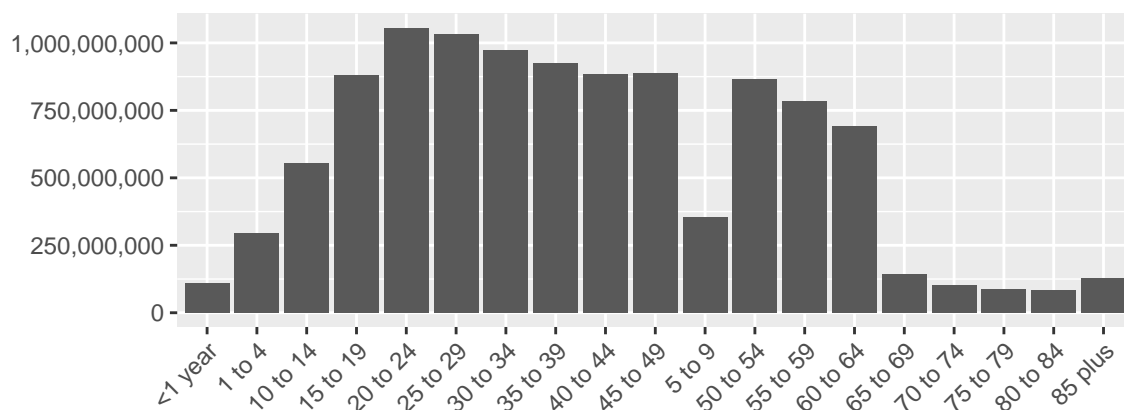
Emergency Department General Expenditures



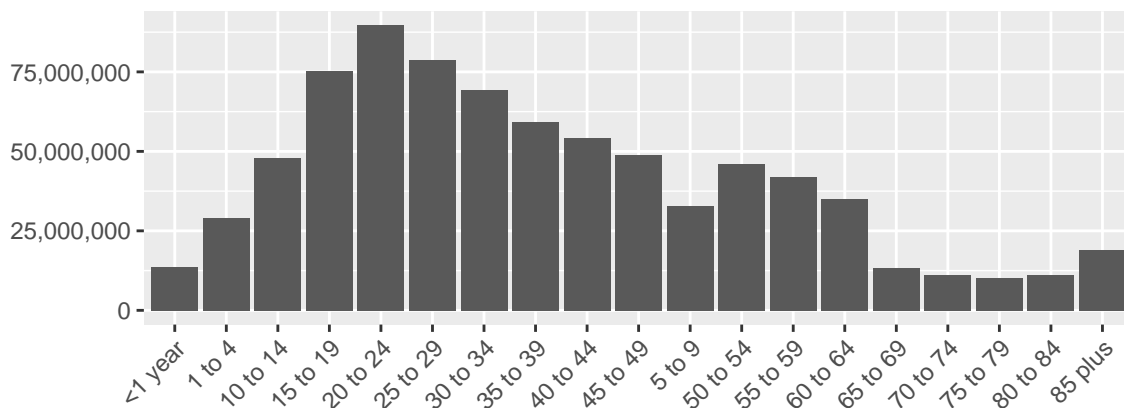
Public Insurance Expenditures



Private Insurance Expenditures



Out of Pocket Expenditures



Gender and Age Interaction

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

```
## # A tibble: 4 x 5
##   term          estimate std.error statistic    p.value
##   <chr>          <dbl>     <dbl>    <dbl>    <dbl>
## 1 (Intercept)  322787054. 12817331.    25.2 1.34e-135
## 2 sexFemale   -137203679. 16852632.    -8.14 4.39e- 16
## 3 sexMale    -194521455. 17120388.   -11.4 9.98e- 30
## 4 age_group_id    805769.  214741.     3.75 1.76e- 4
```

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

```
## [1] 0.01515086
```

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

```
## # A tibble: 6 x 5
##   term                estimate std.error statistic    p.value
##   <chr>              <dbl>    <dbl>    <dbl>    <dbl>
## 1 (Intercept)      314492259. 14399079.    21.8  2.89e-103
## 2 sexFemale        -131585903. 20363372.    -6.46 1.08e- 10
## 3 sexMale          -174461766. 20701440.    -8.43 4.04e- 17
## 4 age_group_id      1183150.    367772.     3.22 1.30e- 3
## 5 sexFemale:age_group_id -255587.    520108.    -0.491 6.23e- 1
## 6 sexMale:age_group_id -912148.    529298.    -1.72 8.49e- 2
```

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

```
## [1] 0.01526663
```

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

```
## # A tibble: 4 x 5
##   term                estimate std.error statistic    p.value
##   <chr>              <dbl>    <dbl>    <dbl>    <dbl>
## 1 (Intercept)      365647683. 16329801.    22.4  2.63e-108
## 2 sexFemale        -152650378. 21470940.    -7.11 1.25e- 12
## 3 sexMale          -182905388. 21812071.    -8.39 5.76e- 17
## 4 age_group_id      -923346.    273589.     -3.37 7.41e- 4
```

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

```
## [1] 0.009269551
```

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

```
## # A tibble: 6 x 5
##   term                estimate std.error statistic    p.value
##   <chr>              <dbl>    <dbl>    <dbl>    <dbl>
## 1 (Intercept)      375087738. 18346775.    20.4  5.58e-91
## 2 sexFemale        -166476777. 25946258.    -6.42 1.46e-10
## 3 sexMale          -197764454. 26377011.    -7.50 7.07e-14
## 4 age_group_id      -1352831.    468601.     -2.89 3.90e- 3
## 5 sexFemale:age_group_id 629046.    662702.     0.949 3.43e- 1
## 6 sexMale:age_group_id 675804.    674412.     1.00 3.16e- 1
```

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

```
## [1] 0.009195668
```

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

```
## # A tibble: 4 x 5
##   term                estimate std.error statistic    p.value
##   <chr>              <dbl>    <dbl>    <dbl>    <dbl>
```

```
## 1 (Intercept)    32685691.  1324847.    24.7  2.22e-130
## 2 sexFemale      -13391357.  1741951.    -7.69 1.65e- 14
## 3 sexMale        -16755207.  1769628.    -9.47 3.52e- 21
## 4 age_group_id   -76424.    22196.     -3.44 5.78e- 4
```

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

```
## [1] 0.01131147
```

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

```
## # A tibble: 6 x 5
```

##	term	estimate	std.error	statistic	p.value
##	<chr>	<dbl>	<dbl>	<dbl>	<dbl>
## 1	(Intercept)	33466867.	1488482.	22.5	3.65e-109
## 2	sexFemale	-14545204.	2105031.	-6.91	5.16e- 12
## 3	sexMale	-17974417.	2139979.	-8.40	5.12e- 17
## 4	age_group_id	-111964.	38018.	-2.95	3.24e- 3
## 5	sexFemale:age_group_id	52495.	53765.	0.976	3.29e- 1
## 6	sexMale:age_group_id	55451.	54715.	1.01	3.11e- 1

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

```
## [1] 0.01124281
```

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(mean_pub ~ agg_cause + age_group_id, data = spending)
tidy(agedismainpub_fit)
```

```
## # A tibble: 16 x 5
```

##	term	estimate	std.error	statistic	p.value
##	<chr>	<dbl>	<dbl>	<dbl>	<dbl>
## 1	(Intercept)	9.95e7	26338094.	3.78	1.58e- 4
## 2	agg_causeCancers	-1.06e8	36673843.	-2.89	3.80e- 3
## 3	agg_causeCardiovascular diseases	4.21e8	36673843.	11.5	2.73e-30
## 4	agg_causeChronic respiratory diseases	1.40e8	37153319.	3.76	1.68e- 4
## 5	agg_causeCommunicable and nutrition ~	2.42e8	36673843.	6.60	4.45e-11
## 6	agg_causeDiabetes and kidney diseases	-9.10e6	36673843.	-0.248	8.04e- 1
## 7	agg_causeDigestive diseases	3.31e8	36673843.	9.02	2.18e-19
## 8	agg_causeEndocrine disorders	-9.14e7	36673843.	-2.49	1.27e- 2
## 9	agg_causeInjuries	4.36e8	36673843.	11.9	1.95e-32
## 10	agg_causeMaternal and neonatal condi~	5.76e7	40412618.	1.43	1.54e- 1
## 11	agg_causeMusculoskeletal conditions	1.07e8	36673843.	2.92	3.51e- 3
## 12	agg_causeNeurological disorders	6.44e7	36673843.	1.76	7.89e- 2

```
## 13 agg_causeOther non-communicable dise~ 1.75e8 36673843. 4.76 1.94e- 6
## 14 agg_causePrevention and coordination -1.13e8 36673843. -3.07 2.16e- 3
## 15 agg_causeSkin and other sense organ ~ 4.52e7 36673843. 1.23 2.17e- 1
## 16 age_group_id 8.06e5 209337. 3.85 1.18e- 4
```

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

```
## [1] 0.06410499
```

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

```
## # A tibble: 30 x 5
```

##	term	estimate	std.error	statistic	p.value
##	<chr>	<dbl>	<dbl>	<dbl>	<dbl>
##	1 (Intercept)	1.24e8	31319834.	3.97	7.24e- 5
##	2 agg_causeCancers	-1.15e8	44292934.	-2.59	9.48e- 3
##	3 agg_causeCardiovascular diseases	3.11e8	44292934.	7.01	2.52e-12
##	4 agg_causeChronic respiratory diseases	1.22e8	44596736.	2.73	6.27e- 3
##	5 agg_causeCommunicable and nutrition ~	2.29e8	44292934.	5.16	2.52e- 7
##	6 agg_causeDiabetes and kidney diseases	-2.30e7	44292934.	-0.519	6.04e- 1
##	7 agg_causeDigestive diseases	3.07e8	44292934.	6.94	4.14e-12
##	8 agg_causeEndocrine disorders	-1.00e8	44292934.	-2.26	2.38e- 2
##	9 agg_causeInjuries	3.72e8	44292934.	8.41	4.70e-17
##	10 agg_causeMaternal and neonatal condi~	7.48e7	49092668.	1.52	1.28e- 1
##	... with 20 more rows				

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

```
## [1] 0.06658248
```

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

```
## # A tibble: 16 x 5
```

##	term	estimate	std.error	statistic	p.value
##	<chr>	<dbl>	<dbl>	<dbl>	<dbl>
##	1 (Intercept)	9.62e7	32854280.	2.93	3.43e- 3
##	2 agg_causeCancers	-6.93e7	45747150.	-1.51	1.30e- 1
##	3 agg_causeCardiovascular diseases	2.20e8	45747150.	4.81	1.53e- 6
##	4 agg_causeChronic respiratory diseas~	1.02e8	46345250.	2.20	2.81e- 2
##	5 agg_causeCommunicable and nutrition~	1.72e8	45747150.	3.76	1.68e- 4
##	6 agg_causeDiabetes and kidney diseas~	-4.50e7	45747150.	-0.984	3.25e- 1
##	7 agg_causeDigestive diseases	4.68e8	45747150.	10.2	2.08e- 24
##	8 agg_causeEndocrine disorders	-5.93e7	45747150.	-1.30	1.95e- 1
##	9 agg_causeInjuries	1.01e9	45747150.	22.1	1.35e-105
##	10 agg_causeMaternal and neonatal cond~	1.33e7	50410918.	0.263	7.93e- 1
##	11 agg_causeMusculoskeletal conditions	1.27e8	45747150.	2.78	5.40e- 3
##	12 agg_causeNeurological disorders	8.64e7	45747150.	1.89	5.91e- 2
##	13 agg_causeOther non-communicable dis~	3.02e8	45747150.	6.61	4.02e- 11
##	14 agg_causePrevention and coordination	-7.12e7	45747150.	-1.56	1.20e- 1
##	15 agg_causeSkin and other sense organ~	8.28e7	45747150.	1.81	7.03e- 2
##	16 age_group_id	-9.24e5	261128.	-3.54	4.05e- 4

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

```
## [1] 0.09747022
```

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

```
## # A tibble: 30 x 5
```

##	term	estimate	std.error	statistic	p.value
##	<chr>	<dbl>	<dbl>	<dbl>	<dbl>
##	1 (Intercept)	8.36e7	39107290.	2.14	3.25e- 2
##	2 agg_causeCancers	-7.68e7	55306060.	-1.39	1.65e- 1
##	3 agg_causeCardiovascular diseases	2.24e8	55306060.	4.04	5.32e- 5
##	4 agg_causeChronic respiratory diseases	1.08e8	55685401.	1.94	5.25e- 2
##	5 agg_causeCommunicable and nutrition ~	1.87e8	55306060.	3.38	7.36e- 4
##	6 agg_causeDiabetes and kidney diseases	-5.10e7	55306060.	-0.923	3.56e- 1
##	7 agg_causeDigestive diseases	5.13e8	55306060.	9.28	2.14e-20
##	8 agg_causeEndocrine disorders	-6.58e7	55306060.	-1.19	2.34e- 1
##	9 agg_causeInjuries	1.11e9	55306060.	20.0	4.57e-87
##	10 agg_causeMaternal and neonatal condi~	1.63e7	61299214.	0.266	7.90e- 1
##	... with 20 more rows				

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

```
## [1] 0.0980724
```

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

```
## # A tibble: 16 x 5
```

##	term	estimate	std.error	statistic	p.value
##	<chr>	<dbl>	<dbl>	<dbl>	<dbl>
##	1 (Intercept)	1.42e7	2686687.	5.28	1.30e- 7
##	2 agg_causeCancers	-1.20e7	3741013.	-3.22	1.30e- 3
##	3 agg_causeCardiovascular diseases	1.03e7	3741013.	2.74	6.11e- 3
##	4 agg_causeChronic respiratory diseases	3.71e6	3789923.	0.979	3.28e- 1
##	5 agg_causeCommunicable and nutrition d~	1.81e7	3741013.	4.85	1.25e- 6
##	6 agg_causeDiabetes and kidney diseases	-8.09e6	3741013.	-2.16	3.06e- 2
##	7 agg_causeDigestive diseases	3.40e7	3741013.	9.08	1.28e-19
##	8 agg_causeEndocrine disorders	-9.97e6	3741013.	-2.67	7.71e- 3
##	9 agg_causeInjuries	6.76e7	3741013.	18.1	9.82e-72
##	10 agg_causeMaternal and neonatal condit~	-3.23e6	4122397.	-0.783	4.34e- 1
##	11 agg_causeMusculoskeletal conditions	5.98e6	3741013.	1.60	1.10e- 1
##	12 agg_causeNeurological disorders	1.64e6	3741013.	0.438	6.62e- 1
##	13 agg_causeOther non-communicable disea~	2.64e7	3741013.	7.06	1.81e-12
##	14 agg_causePrevention and coordination	-1.22e7	3741013.	-3.25	1.16e- 3
##	15 agg_causeSkin and other sense organ d~	2.73e6	3741013.	0.729	4.66e- 1
##	16 age_group_id	-7.65e4	21354.	-3.58	3.43e- 4

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

```
## [1] 0.08494769
```

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

```
## # A tibble: 30 x 5
##   term                                estimate std.error statistic  p.value
##   <chr>                                <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)                        1.37e7  3198930.     4.30  1.75e- 5
## 2 agg_causeCancers                   -1.32e7  4523971.    -2.93  3.42e- 3
## 3 agg_causeCardiovascular diseases    9.34e6  4523971.     2.06  3.90e- 2
## 4 agg_causeChronic respiratory diseases 3.66e6  4555000.     0.803 4.22e- 1
## 5 agg_causeCommunicable and nutrition d~ 1.97e7  4523971.     4.36  1.30e- 5
## 6 agg_causeDiabetes and kidney diseases -9.10e6  4523971.    -2.01  4.44e- 2
## 7 agg_causeDigestive diseases         3.70e7  4523971.     8.17  3.44e-16
## 8 agg_causeEndocrine disorders        -1.10e7  4523971.    -2.44  1.48e- 2
## 9 agg_causeInjuries                  7.30e7  4523971.    16.1  8.26e-58
## 10 agg_causeMaternal and neonatal condit~ -3.29e6  5014204.    -0.657 5.11e- 1
## # ... with 20 more rows
```

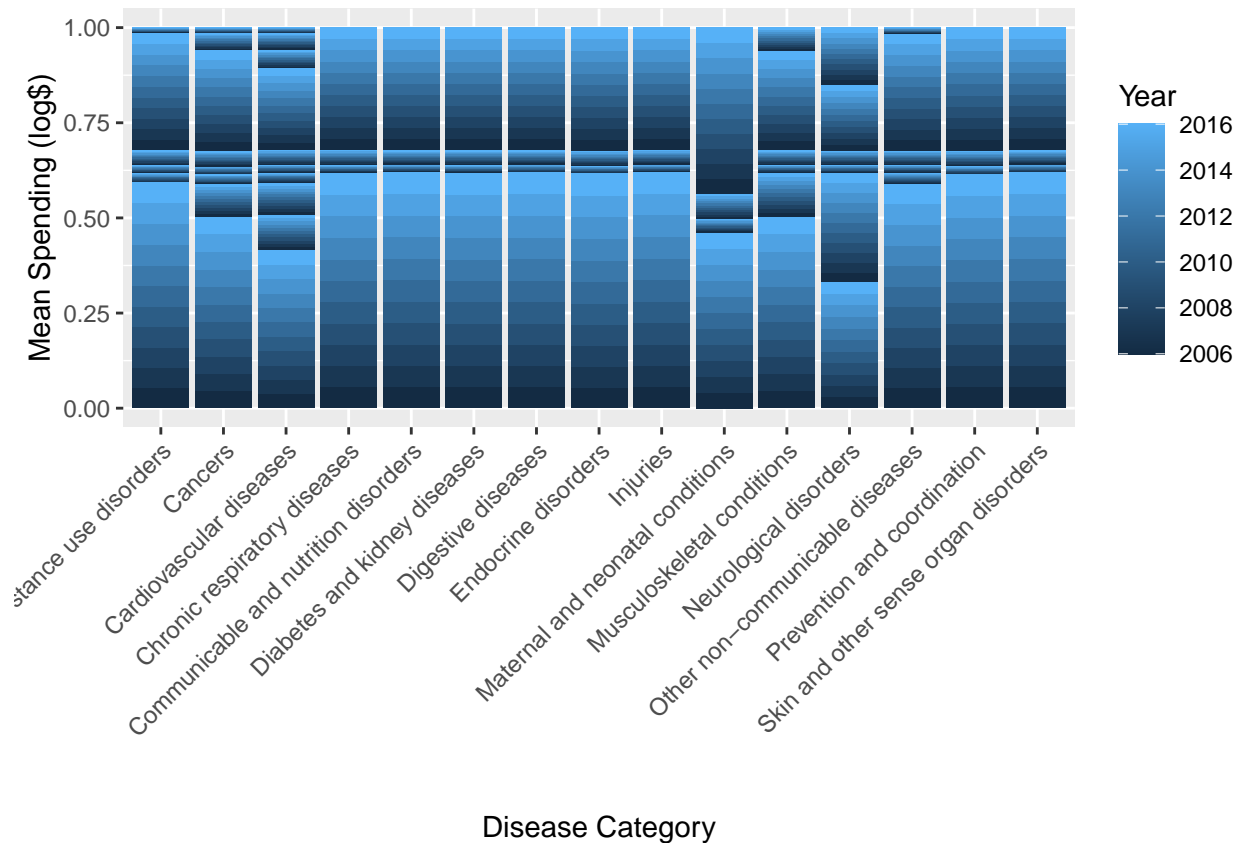
```
glance(agedisinteroop_fit)$adj.r.squared
```

```
## [1] 0.08504477
```

```
##Spending Over Time
```

```
!! I kinda like this but idk if it adds anything but it is fun
```

```
spending %>%
  ggplot(aes(x = agg_cause,
             y = lmean_all,
             fill = year_id)) +
  geom_bar(position = "fill", stat = "identity") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  labs(x = "Disease Category",
       y = "Mean Spending (log$)",
       fill = "Year")
```



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

```
## # A tibble: 2 x 5
##   term      estimate std.error statistic  p.value
##   <chr>      <dbl>    <dbl>    <dbl>    <dbl>
## 1 (Intercept) -91.8      16.0     -5.74 9.95e- 9
## 2 year_id      0.0547    0.00795    6.88 6.57e-12
```