Homework 2: Trip Generation

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Loading the data

I followed the instructions provided in the textbook for loading the data. The following is the R code I used, and the output:

```r
hh <- nhts_households %>%
  # filter to MSA size 2, travel on weekday
  filter(msasize == "02", !travday %in% c("01", "07")) %>%
  # select the columns we care about.
  select(houseid, wthhfin, hhsize, hhvehcnt, numadlt, hhfaminc, wrkcount) %>%
  mutate(
    hhsize = ifelse(hhsize > 4, 4, hhsize),
    hhvehcnt = ifelse(hhvehcnt > 3, 3, hhvehcnt),
    wrkcount = ifelse(wrkcount > 2, 2, wrkcount)
  )

trips <- nhts_trips %>%
  # filter to households in the data
  filter(houseid %in% hh$houseid) %>%
  group_by(houseid, trippurp) %>%
  # count up how many trips each household took
  summarise(trips = n()) %>%
  # "spread" the data, filling zero if no trips were taken
  pivot_wider(id_cols = houseid, names_from = trippurp,
              values_from = trips, values_fill = 0)

# function to change NA to 0
nato0 <- function(x) {ifelse(is.na(x), 0, x)}

tripprod <- hh %>%
  # join tables by id field
  left_join(trips, by = "houseid") %>%
  # change all NA values in columns from the trips data to 0
  mutate_at(vars(names(trips)), nato0)

# Format table
tripprod %>%
  head(n = 10L) %>%
  flextable() %>%
  theme_booktabs() %>%
  align(align = "center", part = "all") %>%
```

```
autofit(add_w = 0, add_h = 0) %>%
fit_to_width(6)
```

houseid	wthhfin	hhsize	hhvehcnt	numadlt	hhfaminc	wrkcount	HBO	HBSHOP	NHB	HBSOCREC	HBW	-9
30000019	279.14359	2	2	2	03	0	4	0	0	0	0	0
30000288	102.84591	1	2	1	05	0	1	1	4	0	0	0
30000289	243.53625	3	3	2	07	1	2	4	3	1	1	0
30000463	347.59831	2	2	2	06	2	7	2	6	0	0	0
30000465	133.01103	4	2	2	08	2	8	2	9	0	1	0
30000478	119.86888	2	0	2	03	0	2	0	0	0	0	0
30000545	35.71683	2	3	2	06	2	0	2	2	4	2	0
30000770	130.37038	1	1	1	06	1	0	3	1	0	1	0
30000983	147.38400	4	3	4	09	1	4	0	2	1	2	0
30001177	303.80186	2	0	2	04	2	3	2	0	2	2	0

2.1

Using this data, we can calculate trip rates by household size and income group:

```
tripprod$hhfaminc <- as_factor(tripprod$hhfaminc) #better data type for manipulation
tripprod <- tripprod %>%
  filter(!hhfaminc %in% c("-7", "-8", "-9")) %>%
  group_by(hhsize, hhfaminc) %>%
  arrange(hhsize, hhfaminc)
tripprod$hhfaminc <- as_label(tripprod$hhfaminc) #to show text instead of numbers

tripprod %>%
  summarize(
    n = n(),
    HBW = weighted.mean(HBW, wthhfin),
    HBSHOP = weighted.mean(HBSHOP, wthhfin),
    HBSOCREC = weighted.mean(HBSOCREC, wthhfin),
    HBO = weighted.mean(HBO, wthhfin),
    NHB = weighted.mean(NHB, wthhfin),
    "\U03A3" = HBW + HBSHOP + HBSOCREC + HBO + NHB
  ) %>%
  #Create table
  flextable() %>%
  theme_booktabs() %>%
  colformat_double(j = 2:9,digits = 2) %>%
  align(align = "center", part = "all") %>%
  autofit(add_w = 0, add_h = 0) %>%
  fit_to_width(6) %>%
  hline(i = seq(11, 44, 11))
```

hhsize	hhfaminc	n	HBW	HBSHOP	HBSOCREC	HBO	NHB	Σ
1	Less than $10,000	323	0.12	0.61	0.35	0.59	0.83	2.51
1	$10,000 to $14,999	333	0.33	0.82	0.31	0.53	1.09	3.08
1	$15,000 to $24,999	512	0.33	0.95	0.43	0.62	1.61	3.94
1	$25,000 to $34,999	476	0.74	0.95	0.50	0.43	1.32	3.94
1	$35,000 to $49,999	503	0.76	0.80	0.37	0.40	1.35	3.68
1	$50,000 to $74,999	499	0.69	0.92	0.35	0.47	2.04	4.47
1	$75,000 to $99,999	261	0.81	1.00	0.70	0.44	1.95	4.91
1	$100,000 to $124,999	135	1.19	0.81	0.36	0.29	1.80	4.45
1	$125,000 to $149,999	58	0.43	0.95	1.33	0.56	1.28	4.55
1	$150,000 to $199,999	42	1.31	0.31	0.21	0.26	1.63	3.72
1	$200,000 or more	57	0.49	0.48	0.49	0.71	1.27	3.44
2	Less than $10,000	122	0.73	2.58	0.48	1.32	4.21	9.31
2	$10,000 to $14,999	119	0.86	2.50	0.58	1.09	2.39	7.43
2	$15,000 to $24,999	268	0.65	1.79	0.53	1.65	3.04	7.65
2	$25,000 to $34,999	398	1.12	1.59	0.69	0.93	1.76	6.09
2	$35,000 to $49,999	582	1.19	1.99	0.81	1.29	2.36	7.63
2	$50,000 to $74,999	882	1.11	1.56	0.77	1.25	2.61	7.31
2	$75,000 to $99,999	744	1.52	1.64	0.58	1.33	3.14	8.22
2	$100,000 to $124,999	504	1.32	1.59	0.85	1.20	3.04	8.01
2	$125,000 to $149,999	275	1.22	2.01	0.64	1.24	3.17	8.30
2	$150,000 to $199,999	259	1.93	1.63	1.52	0.71	2.84	8.63
2	$200,000 or more	264	1.55	1.95	1.16	0.94	2.89	8.49
3	Less than $10,000	51	1.15	1.41	0.23	2.65	1.96	7.40
3	$10,000 to $14,999	40	0.67	3.11	0.45	1.51	4.17	9.91
3	$15,000 to $24,999	83	1.35	0.88	0.33	2.39	2.20	7.15
3	$25,000 to $34,999	97	1.54	1.66	0.96	1.36	2.08	7.61
3	$35,000 to $49,999	119	2.33	1.50	1.03	2.17	2.54	9.58
3	$50,000 to $74,999	222	2.01	1.82	0.88	2.15	3.66	10.52
3	$75,000 to $99,999	182	2.26	1.48	0.77	1.62	3.23	9.36
3	$100,000 to $124,999	130	1.73	1.85	1.49	2.29	6.10	13.47
3	$125,000 to $149,999	87	2.57	2.93	1.31	1.39	2.45	10.65
3	$150,000 to $199,999	68	2.15	1.07	1.45	0.94	2.94	8.55
3	$200,000 or more	66	2.11	2.25	1.53	2.45	3.41	11.76
4	Less than $10,000	50	0.62	1.53	1.19	4.63	3.06	11.02
4	$10,000 to $14,999	28	0.98	2.37	0.67	2.33	1.87	8.22

hhsize	hhfaminc	n	HBW	HBSHOP	HBSOCREC	HBO	NHB	Σ
4	$15,000 to $24,999	70	1.20	1.72	0.43	7.13	5.20	15.70
4	$25,000 to $34,999	100	1.55	1.98	1.06	5.20	3.12	12.91
4	$35,000 to $49,999	124	1.94	1.42	0.98	3.50	4.36	12.20
4	$50,000 to $74,999	222	1.94	1.72	1.32	3.89	4.10	12.97
4	$75,000 to $99,999	197	2.31	1.13	0.96	3.94	3.40	11.75
4	$100,000 to $124,999	164	2.32	2.22	1.04	4.12	3.80	13.50
4	$125,000 to $149,999	103	2.41	2.06	1.29	4.81	5.24	15.80
4	$150,000 to $199,999	100	1.50	2.50	2.09	5.97	6.64	18.69
4	$200,000 or more	88	1.99	1.16	2.59	3.17	4.89	13.80

Generally, this data seems to make sense: a larger household size will produce more trips, and a higher income roughly will produce more trips as well. In most of the household sizes, the HBW (and total) trip rates peak somewhere around the $150,000 range, which makes sense as after a certain level of income, possibly fewer trips are needed as more executive positions may be easier to do remotely. The HBSOCREC trips also increase generally with income, which makes sense, though there are quite a few specific numbers that don't follow this trend. Most of these are from groups with small sample sizes however, so the exact numbers may not represent a realistic average.

2.2

We can use a similar process to calculate trip rates by household workers and vehicles:

```
tripprod %>%
  group_by(wrkcount, hhvehcnt) %>%
  arrange(wrkcount, hhvehcnt) %>%
  summarize(
    n = n(),
    HBW = weighted.mean(HBW, wthhfin),
    HBSHOP = weighted.mean(HBSHOP, wthhfin),
    HBSOCREC = weighted.mean(HBSOCREC, wthhfin),
    HBO = weighted.mean(HBO, wthhfin),
    NHB = weighted.mean(NHB, wthhfin),
    "\U03A3" = HBW + HBSHOP + HBSOCREC + HBO + NHB
  ) %>%
  flextable() %>%
  theme_booktabs() %>%
  colformat_double(j = 3:9,digits = 2) %>%
  align(align = "center", part = "all") %>%
  autofit(add_w = 0, add_h = 0) %>%
  fit_to_width(6)
```

wrkcount	hhvehcnt	n	HBW	HBSHOP	HBSOCREC	HBO	NHB	Σ
0	0	318	0.01	0.83	0.42	0.94	0.87	3.06
0	1	1,652	0.01	1.36	0.61	1.47	1.71	5.17
0	2	1,240	0.06	2.03	0.99	1.46	2.25	6.79
0	3	472	0.03	2.47	1.01	1.90	2.52	7.92
1	0	79	0.50	1.70	0.16	0.59	0.95	3.90
1	1	1,387	1.00	1.13	0.51	1.49	2.25	6.38
1	2	1,268	1.21	1.58	0.79	2.14	2.72	8.43
1	3	760	1.03	1.89	1.13	2.10	3.06	9.22
2	0	8	3.79	2.43	1.12	1.97	1.64	10.94
2	1	153	2.07	1.92	0.35	1.85	3.06	9.24
2	2	1,360	2.30	1.53	0.74	2.32	3.43	10.32
2	3	1,310	2.59	1.53	1.22	2.54	4.22	12.09

This data also roughly makes sense, as trips go up with number of workers and number of vehicles. However, there are some unexpected data points: as an example, a 2-worker 0-vehicle (2W0V) household makes almost twice as many HBW trips as a 2W1V household. I can think of two things that might contribute to this though: the very small number of observations for the 2W0V category (which can introduce statistical error), and that with a car it is much more likely for workers to stop at a different activity on their way to or from work than if they were relying on transit or walking/biking. Overall, the data seems to be mostly good, but may require some tweaking to achieve more realistic numbers.

2.3

We can calculate the standard deviation in trip rates by household size/vehicle count and number of workers/vehicle count:

```r
size <- tripprod %>%
  group_by(hhsize, hhvehcnt) %>%
  arrange(hhsize, hhvehcnt) %>%
  summarise(HBW = wtd.sd(HBW, wthhfin)) %>%
  pivot_wider(names_from = hhsize, values_from = HBW)
emp <- tripprod %>%
  group_by(wrkcount, hhvehcnt) %>%
  arrange(wrkcount, hhvehcnt) %>%
  summarise(HBW = wtd.sd(HBW, wthhfin)) %>%
  pivot_wider(names_from = wrkcount, values_from = HBW)

left_join(size, emp, by = "hhvehcnt") %>%
  format_my_table() %>%  #Custom function to avoid clutter
  set_caption("Weighted standard deviations of HBW trips",
              autonum = F)
```

Table 4: Weighted standard deviations of HBW trips

	Size				Workers		
Household Vehicles	1	2	3	4	0	1	2
0	0.32	0.63	1.04	1.73	0.10	0.81	2.03
1	0.85	1.23	1.15	1.36	0.16	0.95	1.69
2	1.08	1.49	1.54	1.46	0.40	1.03	1.56
3	0.76	1.53	1.80	1.85	0.22	0.97	1.76

Some of these standard deviations are quite small relative to the trip rate, but a lot are fairly large, and many even exceed the trip rate itself. This is somewhat to be expected though, given the small sample size of many of the categories (see Problem 2.4). For estimating work trips, it may make sense to use the number of workers rather than the household size, but since all other trip types are estimated based on household size, it would be practical to do the same for work trips. Both household size and worker count seem to correlate well enough that it shouldn't make a drastic difference in the model.

2.4

We can use a similar process to find the number of trips in each category:

```r
size <- tripprod %>%
  group_by(hhsize, hhvehcnt) %>%
  arrange(hhsize, hhvehcnt) %>%
  summarise(n = n()) %>%
  pivot_wider(names_from = hhsize, values_from = n)
emp <- tripprod %>%
  group_by(wrkcount, hhvehcnt) %>%
  arrange(wrkcount, hhvehcnt) %>%
  summarise(n = n()) %>%
  pivot_wider(names_from = wrkcount, values_from = n)
```

```
left_join(size, emp, by = "hhvehcnt") %>%
  format_my_table() %>%  #Custom function to avoid clutter
  set_caption("Number of households in each classification",
              autonum = F)
```

Table 5: Number of households in each classification

Household Vehicles	Size				Workers		
	1	2	3	4	0	1	2
0	317	53	24	11	318	79	8
1	2,160	755	159	118	1,652	1,387	153
2	520	2,382	415	551	1,240	1,268	1,360
3	202	1,227	547	566	472	760	1,310

Clearly some of the household types have very few observations, which (at least partly) explains why many of the data points in the previous problems don't always make sense. For example, there are 8 0-vehicle/2-worker households out of the thousands of total households, which is not at all a large enough sample size to generate any meaningful trip rates. However, trip rates for these households can likely be estimated to somewhat realistic values using the rest of the data, and in fact may already represent realistic values, even if the confidence intervals are quite wide.

2.5

In order to create trip attraction models, first we need to download the PSRC data with trip attractions and other useful variables by tract:

```
psrc_attractions <- read_csv(
  "https://byu.box.com/shared/static/7ci8vomip719bdno7xl5ftjj940dausm.csv"
  )
```

Now we can estimate models for trip attraction based on these variables:

```
lm(data = psrc_attractions, HBW ~ tothh + retl + manu + offi + gved + othr + totemp) %>%
  summary()
```

```
##
## Call:
## lm(formula = HBW ~ tothh + retl + manu + offi + gved + othr +
##     totemp, data = psrc_attractions)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -25895  -2210  -1078    -55  55606
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1767.6703   763.5193  -2.315  0.02092 *
## tothh          1.0838     0.3523   3.076  0.00219 **
## retl          -0.2853     0.5407  -0.528  0.59793
## manu          -1.2681     0.5813  -2.181  0.02951 *
```

```
## offi              1.0069      0.2112    4.768 2.31e-06 ***
## gved              1.7652      0.2463    7.167 2.14e-12 ***
## othr              0.3414      0.4192    0.815  0.41566
## totemp            0.2719      0.1782    1.526  0.12749
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6348 on 634 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:   0.53,  Adjusted R-squared:  0.5248
## F-statistic: 102.1 on 7 and 634 DF,  p-value: < 2.2e-16
```

Looking at these estimates presents a few immediate problems: for one, the coefficients for retail and manufacturing jobs are negative, and the intercept is very low as well, implying a TAZ with no jobs or households would attract -1768 trips. I also included total employment as well as each employment type variable, which doesn't make too much sense.

After some experimentation, these are the models I settled on:

```
HBWlm <- lm(data = psrc_attractions, HBW ~ totemp)
summary(HBWlm)
```

```
##
## Call:
## lm(formula = HBW ~ totemp, data = psrc_attractions)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -41447  -1955  -1180   -699  56593
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 530.34960  300.96059   1.762   0.0785 .
## totemp        0.98197    0.04386  22.388   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6902 on 640 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.4392, Adjusted R-squared:  0.4383
## F-statistic: 501.2 on 1 and 640 DF,  p-value: < 2.2e-16
```

```
HBShoplm <- lm(data = psrc_attractions, HBShop ~ retl)
summary(HBShoplm)
```

```
##
## Call:
## lm(formula = HBShop ~ retl, data = psrc_attractions)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -8166  -1081   -850   -500  61128
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 850.1453   192.1419   4.425 1.14e-05 ***
```

```
## retl            2.1668      0.2878    7.529 1.75e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4425 on 640 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.08136,    Adjusted R-squared:  0.07993
## F-statistic: 56.68 on 1 and 640 DF,  p-value: 1.748e-13
```

```
HBOlm <- lm(data = psrc_attractions, HBO ~ tothh + retl)
summary(HBOlm)
```

```
##
## Call:
## lm(formula = HBO ~ tothh + retl, data = psrc_attractions)
##
## Residuals:
##     Min     1Q Median     3Q    Max
## -19611  -6352  -4188   -875 227814
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   36.4578  1974.1600    0.018 0.985272
## tothh          3.1047     0.9095    3.414 0.000682 ***
## retl           5.2740     1.1281    4.675 3.59e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 17100 on 639 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.05878,    Adjusted R-squared:  0.05584
## F-statistic: 19.95 on 2 and 639 DF,  p-value: 3.926e-09
```

```
NHBlm <- lm(data = psrc_attractions, NHB ~ retl + offi + gved)
summary(NHBlm)
```

```
##
## Call:
## lm(formula = NHB ~ retl + offi + gved, data = psrc_attractions)
##
## Residuals:
##     Min     1Q Median     3Q    Max
## -67515  -2587  -1517      3 126083
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 1083.3339   451.0657    2.402  0.01660 *
## retl           2.5002     0.7846    3.187  0.00151 **
## offi           1.7142     0.1265   13.555  < 2e-16 ***
## gved           1.1127     0.2713    4.102 4.64e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10120 on 638 degrees of freedom
##   (1 observation deleted due to missingness)
```

```
## Multiple R-squared:  0.3901, Adjusted R-squared:  0.3873
## F-statistic:    136 on 3 and 638 DF,  p-value: < 2.2e-16
```

2.6

Most of these trip attraction models seem to be reasonable: work trips correlate with employment, shopping with retail, etc. NHB trips correlate with certain types of employment and retail, suggesting that office and government employees are likely to go shopping right after work. Manufacturing jobs didn't correlate well with NHB trips though, and I would suspect this has to do with income (manufacturing jobs can often pay less than office jobs), though there may be other factors as well.

None of the R^2 values are particularly good, but the HBW model has a decent R^2 of 0.44. The only significant variable that HBW trips correlated well with was total employment, which makes sense and would largely explain the relatively high R^2 value.

2.7

Here are the models with the intercept removed:

```
HBWlmNI <- lm(data = psrc_attractions, HBW ~ totemp - 1)
summary(HBWlmNI)
```

```
##
## Call:
## lm(formula = HBW ~ totemp - 1, data = psrc_attractions)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -42491  -1478   -673   -191  56993
##
## Coefficients:
##        Estimate Std. Error t value Pr(>|t|)
## totemp  1.01484    0.03976   25.52   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6913 on 641 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.504,  Adjusted R-squared:  0.5033
## F-statistic: 651.4 on 1 and 641 DF,  p-value: < 2.2e-16
```

```
HBShoplmNI <- lm(data = psrc_attractions, HBShop ~ retl - 1)
summary(HBShoplmNI)
```

```
##
## Call:
## lm(formula = HBShop ~ retl - 1, data = psrc_attractions)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -10001   -335      0    274  61582
##
## Coefficients:
##      Estimate Std. Error t value Pr(>|t|)
## retl   2.6979     0.2653   10.17   <2e-16 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4489 on 641 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.1389, Adjusted R-squared:  0.1375
## F-statistic: 103.4 on 1 and 641 DF,  p-value: < 2.2e-16
```
```r
HBOlmNI <- lm(data = psrc_attractions, HBO ~ tothh + retl - 1)
summary(HBOlmNI)
```
```
##
## Call:
## lm(formula = HBO ~ tothh + retl - 1, data = psrc_attractions)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -19610   -6343   -4175    -865  227793
##
## Coefficients:
##       Estimate Std. Error t value Pr(>|t|)
## tothh   3.1203     0.3419   9.126  < 2e-16 ***
## retl    5.2740     1.1273   4.679 3.53e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 17090 on 640 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.2177, Adjusted R-squared:  0.2152
## F-statistic: 89.03 on 2 and 640 DF,  p-value: < 2.2e-16
```
```r
NHBlmNI <- lm(data = psrc_attractions, NHB ~ retl + offi + gved - 1)
summary(NHBlmNI)
```
```
##
## Call:
## lm(formula = NHB ~ retl + offi + gved - 1, data = psrc_attractions)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -68405   -1680    -527     930  122890
##
## Coefficients:
##       Estimate Std. Error t value Pr(>|t|)
## retl    2.9718     0.7625   3.898 0.000107 ***
## offi    1.7506     0.1260  13.891  < 2e-16 ***
## gved    1.2214     0.2685   4.549 6.45e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10160 on 639 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.4606, Adjusted R-squared:  0.4581
## F-statistic: 181.9 on 3 and 639 DF,  p-value: < 2.2e-16
```

All of the R^2 values increased with the intercept removed, but this is misleading, as the R^2 value is now

comparing against a random guess for the trip rates rather than against the average trip rates. Basically these R^2 values are meaningless, and we should definitely keep the intercept in. However, it may be wise to use a piecewise linear model in order to account for the fact that sparse TAZs would attract close to zero trips, rather than the intercept's number of trips. However, that is outside the scope of the assignment, so will not be done here.