Advanced Analytics Capstone
CSDA 1050

Sprint 3 Report
Housing Rent Prices for 2-bedroom apartments in the major Canadian Cities

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Introduction:

We will be evaluating the cost of living for renters in the major Canadian Cities. This information will provide a better understanding of what drives rent costs. The focus will be to find fact-based insights on meaningful patterns in the housing rental market. Owning a home is an ideal need for young adults in Canada and the social pressures along with increasing opportunities for profit, were driving the growth of the market, causing first time home buyers to struggle in finding a place to live at a reasonable price. Which forces most young adults to rent rather than owning their own home.

About the data set:

The datasets were gathered from third-party external source from the Canadian Mortgage and Housing Corporation website. The datasets include Average Income After Tax Renters, Average Rent 2 Bedrooms and Housing market Indicators. They can be found using these links below:

https://www.cmhc-schl.gc.ca/en/data-and-research/data-tables/real-average-after-tax-

https://www.cmhc-schl.gc.ca/en/data-and-research/data-tables/average-rent-2-bedroom-

https://www.cmhc-schl.gc.ca/en/data-and-research/data-tables/housing-market-indicators

Objective:

Our objective is to determine the most cost-effective price for renter's base on their household income. Even though factors, such as rise in unemployment rates increase in some of Canada's major cities, housing prices are still rising. Renting has started to consume over 50% of the average household's monthly income. We conclude that with increases in household debt, stagnant wages and expected rises in interest rates, a decline is inevitable. These factors are also forcing home buyers sell their homes and go back to renting.

Overview

Our analysis has been carefully explained to its simplest form to accommodate stakeholders that may not understand various analytical terms. Each step was carefully explained and visualized.

Loading some of the Libraries

In [1]:
```
# Loading packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import os
from pandas import read_table
from scipy.stats import norm
%matplotlib inline
```

Preparing the Average price per 2 bedrooms data

```
In [63]: # Importing the Renter Household data
         rent= pd.read_csv(r"C:\\Users\\susie\\Documents\\Data Science\\Capstone data\\Average price 2 bedrooms.csv"
                           ,encoding="latin")
         rent.head(5)
```

Out[63]:

	City	1992	1993	1994	1995	1996	1997	1998	1999	2000	...	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
0	St. JohnÕs	566.0	554.0	559.0	565.0	570.0	567.0	513.0	517.0	552.0	...	614.0	630.0	677.0	725.0	771.0	798.0	864.0	888.0	923.0	958.0
1	Halifax	595.0	604.0	610.0	615.0	617.0	616.0	631.0	637.0	648.0	...	815.0	833.0	877.0	891.0	925.0	954.0	976.0	1005.0	1048.0	1063.0
2	Moncton	469.0	479.0	495.0	504.0	513.0	523.0	531.0	538.0	560.0	...	643.0	656.0	675.0	691.0	715.0	731.0	742.0	762.0	760.0	798.0
3	Saint John	429.0	436.0	439.0	437.0	441.0	449.0	452.0	457.0	460.0	...	570.0	618.0	644.0	645.0	670.0	691.0	691.0	714.0	718.0	720.0
4	Saguenay	420.0	419.0	416.0	417.0	423.0	425.0	428.0	428.0	438.0	...	490.0	518.0	518.0	535.0	557.0	549.0	571.0	595.0	598.0	587.0

5 rows × 26 columns

5 rows × 26 columns

Looking at the data above, it seems, we only have mostly numeric values only one column has objects.

Rent data Columns

```
In [72]: rent.columns

Out[72]: Index(['City', '1992', '1993', '1994', '1995', '1996', '1997', '1998', '1999',
                '2000', '2001', '2002', '2003', '2004', '2005', '2006', '2007', '2008',
                '2009', '2010', '2011', '2012', '2013', '2014', '2015', '2016'],
               dtype='object')
```

Top 10 most expensive cities

Finding the to 10 hightest and lowest rent prices for 2 bedroom apartments.

```
In [46]: # Using the n.largest I will search the data to find the highest prices for 2 bedroom apartments.
         lrg = rent.nlargest(10, ['1992', '1993', '1994', '1995', '1996', '1997', '1998', '1999',
                '2000', '2001', '2002', '2003', '2004', '2005', '2006', '2007', '2008',
                '2009', '2010', '2011', '2012', '2013', '2014', '2015', '2016'])
         lrg
```

Out[46]:

	City	1992	1993	1994	1995	1996	1997	1998	1999	2000	...	2007	2008	2009	2010	2011	2012	2013	2014	2015	20
31	Vancouver	771.0	790.0	812.0	826.0	845.0	852.0	870.0	864.0	890.0	...	1084.0	1124.0	1169.0	1195.0	1237.0	1261.0	1281.0	1311.0	1368.0	145
13	Toronto	754.0	773.0	784.0	805.0	819.0	821.0	881.0	916.0	979.0	...	1061.0	1095.0	1096.0	1123.0	1149.0	1183.0	1213.0	1251.0	1288.0	1327
9	Ottawa	700.0	727.0	738.0	738.0	739.0	729.0	754.0	783.0	877.0	...	961.0	995.0	1028.0	1048.0	1086.0	1115.0	1132.0	1132.0	1174.0	120
32	Victoria	684.0	703.0	713.0	715.0	717.0	724.0	722.0	728.0	731.0	...	907.0	965.0	1001.0	1024.0	1045.0	1059.0	1068.0	1095.0	1128.0	118
21	Barrie	653.0	670.0	687.0	712.0	713.0	737.0	774.0	788.0	830.0	...	934.0	954.0	961.0	968.0	1001.0	1037.0	1048.0	1118.0	1167.0	115
12	Oshawa	651.0	659.0	659.0	689.0	700.0	691.0	726.0	745.0	778.0	...	877.0	889.0	900.0	903.0	941.0	939.0	985.0	1010.0	1035.0	110
23	Thunder Bay	620.0	632.0	655.0	659.0	672.0	666.0	647.0	647.0	654.0	...	709.0	719.0	742.0	763.0	772.0	818.0	858.0	888.0	917.0	94
20	Windsor	620.0	631.0	643.0	667.0	682.0	680.0	680.0	696.0	736.0	...	773.0	772.0	747.0	752.0	753.0	778.0	788.0	798.0	824.0	85
18	Guelph	618.0	626.0	642.0	642.0	658.0	678.0	686.0	702.0	736.0	...	848.0	869.0	874.0	887.0	903.0	941.0	957.0	988.0	1027.0	107
30	Abbotsford-Mission	615.0	635.0	640.0	651.0	645.0	628.0	633.0	630.0	632.0	...	752.0	765.0	781.0	785.0	800.0	818.0	820.0	835.0	864.0	91

From the output above the most expensive cities are Vancouver, Toronto, Ottawa, Victoria, Barrie, Oshawa, Thunder Bay, Windsor, Guelph and Abbotsford Mission.

The top 10 least expensive cities

Here we are filtering the rent dataset to find the top 10 least expensive cities

In [47]:
```
# The .nsmallest was used t get the cities with the lowest prices for 2 bedroom apartments
sml = rent.nsmallest(10, ['1992', '1993', '1994', '1995', '1996', '1997', '1998', '1999',
       '2000', '2001', '2002', '2003', '2004', '2005', '2006', '2007', '2008',
       '2009', '2010', '2011', '2012', '2013', '2014', '2015', '2016'])
sml
```

Out[47]:

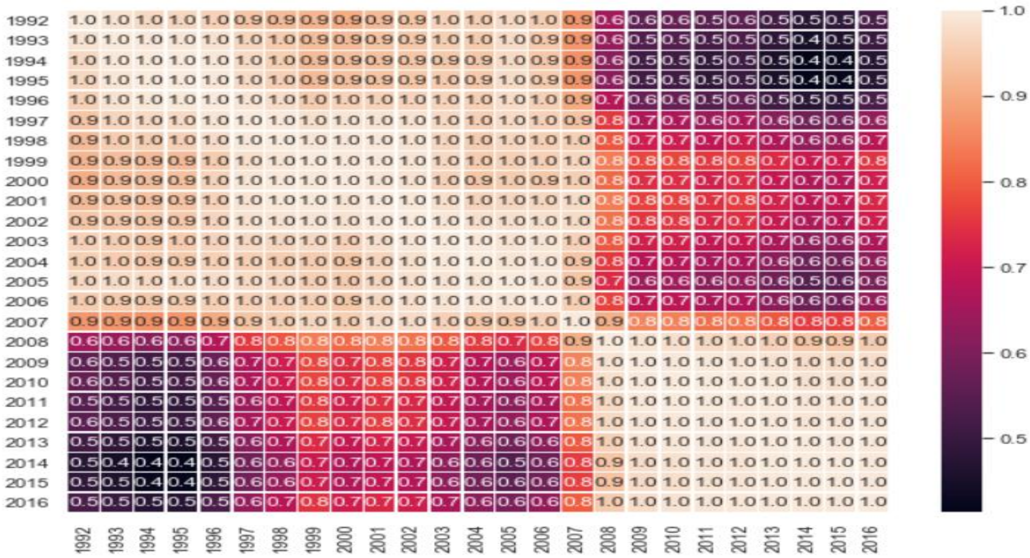
	City	1992	1993	1994	1995	1996	1997	1998	1999	2000	...	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
6	Trois-Rivi□res	395.0	400.0	402.0	406.0	405.0	406.0	411.0	403.0	413.0	...	487.0	505.0	520.0	533.0	547.0	550.0	555.0	568.0	581.0	587.0
5	Sherbrooke	408.0	418.0	420.0	422.0	426.0	426.0	433.0	434.0	437.0	...	529.0	543.0	553.0	566.0	577.0	578.0	591.0	604.0	608.0	622.0
4	Saguenay	420.0	419.0	416.0	417.0	423.0	425.0	428.0	428.0	438.0	...	490.0	518.0	518.0	535.0	557.0	549.0	571.0	595.0	598.0	587.0
3	Saint John	429.0	436.0	439.0	437.0	441.0	449.0	452.0	457.0	460.0	...	570.0	618.0	644.0	645.0	670.0	691.0	691.0	714.0	718.0	720.0
26	Saskatoon	444.0	449.0	452.0	460.0	479.0	500.0	516.0	529.0	541.0	...	693.0	841.0	905.0	934.0	966.0	1002.0	1041.0	1091.0	1087.0	1100.0
2	Moncton	469.0	479.0	495.0	504.0	513.0	523.0	531.0	538.0	560.0	...	643.0	656.0	675.0	691.0	715.0	731.0	742.0	762.0	760.0	798.0
25	Regina	484.0	487.0	485.0	487.0	494.0	512.0	525.0	547.0	549.0	...	661.0	756.0	832.0	881.0	932.0	979.0	1018.0	1079.0	1097.0	1109.0
7	Montr□al	488.0	484.0	484.0	494.0	491.0	491.0	499.0	506.0	509.0	...	647.0	659.0	669.0	700.0	719.0	711.0	730.0	739.0	760.0	791.0
8	Gatineau	513.0	519.0	528.0	536.0	537.0	530.0	529.0	534.0	544.0	...	662.0	677.0	690.0	711.0	731.0	743.0	744.0	750.0	751.0	762.0
17	Brantford	541.0	572.0	593.0	606.0	610.0	612.0	617.0	614.0	639.0	...	749.0	752.0	754.0	778.0	792.0	838.0	835.0	855.0	870.0	908.0

10 rows × 26 columns

The Top 10 least expensive cities are Tros-Rivers, Sherbrooke, Saguenay, Saint John, Saskatoon, Moncton, Regina, Montreal, Ga and Bradford. We will be focusing on the least expensive rent prices since our research question is to figure out the most livable cities.

Correlation plot for the sml data values

```
# Plotting the correlation data to get a better visual on the graph
f,ax = plt.subplots(figsize=(10,8))
sns.heatmap(sml.corr(), annot = True,linewidths=.4, fmt='.1f', ax=ax)
plt.show()
```



In the correlation heatmap it seems as though 2001, 2002,1999 and 2000 have the strongest correlation.

Renaming the variables that will be used for modelling

```
In [6]: #Renaming 2001 column name
        sml.rename(columns={'2001': 'price1'}, inplace=True)
```

```
In [8]: # Renameing 2007 column name
        sml.rename(columns={'2002': 'price2'}, inplace=True)
```

```
In [9]: # Renameing 2007 column name
        sml.rename(columns={'1999': 'price99'}, inplace=True)
```

These variables are much easier to work with if they are renamed, because the column names were numbers, we might run into issues later if they aren't renamed before hand.

Checking for outliers

There are certain things, if not done in the EDA phase, can affect further statistical Machine Learning modelling. One of them is finding outliers. We will be using Box plots to help us detect outliers. Box plot is a method for graphically depicting groups of numerical data through their quartiles. They may also have lines extending vertically or horizontally from the indicating variability outside the upper and lower quartiles.

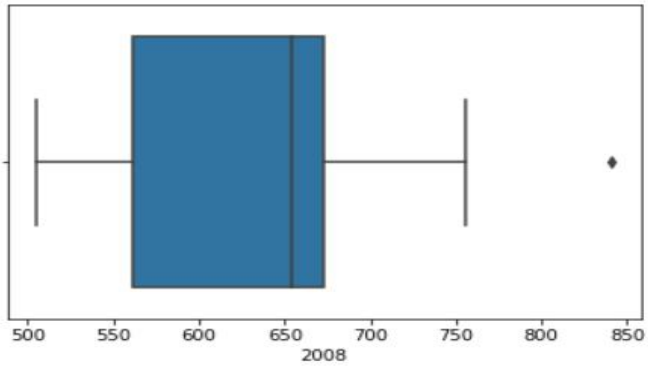
```
In [96]: sml.plot(kind='box', figsize=(15,8))
Out[96]: <matplotlib.axes._subplots.AxesSubplot at 0x2d6d3eba160>
```

Looking at the graph above there seem to several outliers in the sml dataset from 2008 to 2016 we will take a closer look below.

Identifying the outliers

Before we try to understand whether to ignore the outliers or not, we need to know ways to identify them. Mostly we will try to see visualization methods rather mathematical. Outliers may be plotted as individual points.

```
In [232]: # identify the outlier in 2018
          sns.boxplot(sml['2008'])
Out[232]: <matplotlib.axes._subplots.AxesSubplot at 0x1f73cb43198>
```



Above plot shows 2008 has one point between 800 to 850, the outlier is not included in the box of other observation nowhere near the quartiles. This we will remove, and the same process will be repeated to clean any outlier in the dataset.

Removing Outlier

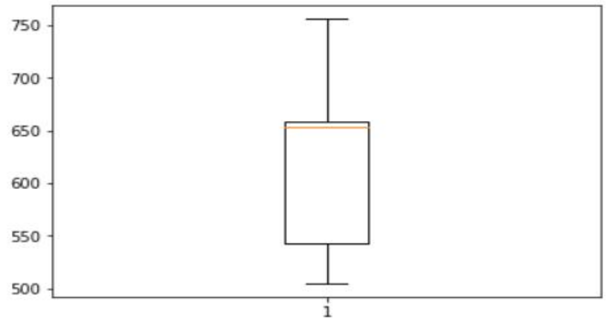
```
[234]:
# Identifyng and removig the outliers from the 2008 values
from numpy import percentile

# calculate interquartile range
q25, q75 = percentile(data, 25), percentile(data, 75)
iqr = q75 - q25
print('Percentiles: 25th=%.3f, 75th=%.3f, IQR=%.3f' % (q25, q75, iqr))
# calculate the outlier cutoff
cut_off = iqr * 1.5
lower, upper = q25 - cut_off, q75 + cut_off
# identify outliers
outliers = [x for x in data if x < lower or x > upper]
print('Identified outliers: %d' % len(outliers))
# remove outliers
removed = [x for x in data if x >= lower and x <= upper]
print('Non-outlier observations: %d' % len(removed))

Percentiles: 25th=561.750, 75th=672.500, IQR=110.750
Identified outliers: 1
Non-outlier observations: 9
```

In the 2008 feature there are 9 non-outlier and one outlier that was identified.

Clean data

Here is the result of the cleaned data after the outlier was removed if there is an outlier it will plotted as point in boxplot, but other population will be grouped together and display as box. Let’s try and see it ourselves.

In [236]:
```
# plot showing the 2008 clean data values
plt.boxplot(removed)
plt.show()
```

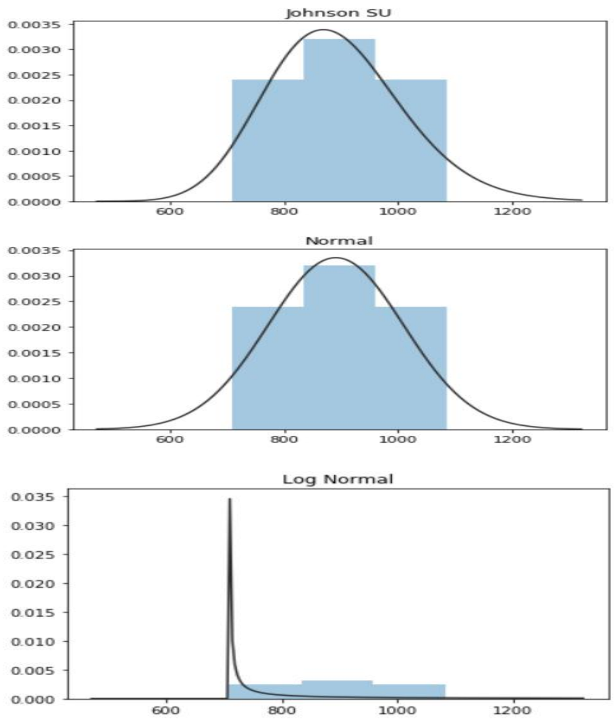


Even though there was an outlier it seems as though it didn't affected the mean price it remained the same before and after the outlier was removed at around 650.

Johnson SU distribution plot

The mu and sigma are the mean and the standard deviation of the distribution. The Johnson plot is a transformation of the normal distribution the Johnson SU was developed to in order to apply the established methods and theory of the normal distribution to non-normal datasets.

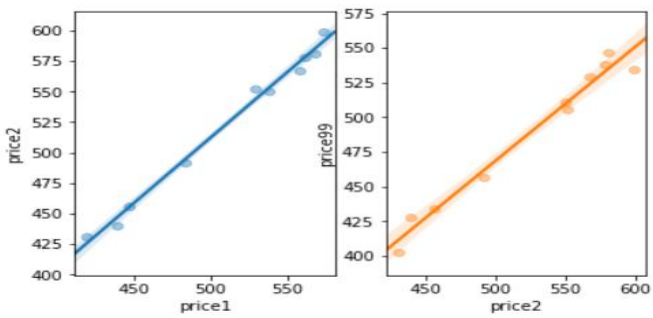
<matplotlib.axes._subplots.AxesSubplot at 0x1f73f4f8390>



Regression Plot

The line of best fit is calculated by minimizing the ordinary least squares error function, that Seaborn module does automatically using the regplot function. The shaded area around the line represents 95% confidence intervals. When running a regression, statwing automatically calculates and plots residuals to help understand and improve the regression model.

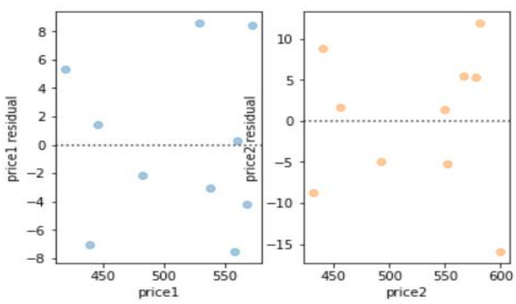
```
In [18]: # Regression plot
         fig, ax = plt.subplots(1,2)
         sns.regplot('price1','price2',sml, ax=ax[0], scatter_kws={'alpha':0.4})
         sns.regplot('price2','price99',sml,ax=ax[1], scatter_kws={'alpha':0.4})

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x218db4cc9b0>
```



As you can see from the above plots our data is very clean the points on the model are almost perfect.

Residual Plot

```
In [20]: # visualizing the residuals by creating residual plots .
         fig, ax = plt.subplots(1,2)
         ax[0]= sns.residplot('price1','price2', sml,ax=ax[0], scatter_kws={'alpha':0.4})
         ax[0].set_ylabel('price1 residual')
         ax[1]=sns.residplot('price2','price99',sml,ax=ax[1], scatter_kws={'alpha':0.4})
         ax[1].set_ylabel('price2 residual')

Out[20]: Text(0, 0.5, 'price2 residual')
```



The points in the residual plot represent the difference between the sample (y) and the predicted value (y'). Residuals that are greater than zero are points that are underestimated by the model and residuals less than zero are points that are overestimated by the model.

Creating a fitted linear model

```
In [259]: # create a fitted model
          import statsmodels.formula.api as smf
          model = smf.ols(formula='price1 ~ price2', data=sml).fit()

          # print the coefficients
          lm1.params

Out[259]: Intercept    12.191914
          price2        0.952636
          dtype: float64
```

```
In [ ]: # The price for rent seem to have increased by $95.26 from 2001 to 2002
```

The price for rent seem to have increased by $95.26 from 2001 to 2002

P Values

```
In [260]: # print the p-values for the model coefficients
          #Represents the probability that the coefficient is actually zero

          lm1.pvalues

Out[260]: Intercept    4.506910e-01
          price2       6.838871e-10
          dtype: float64
```

P values represents the probability that the coefficient is actually zero.

R Square

```
In [232]: # print the R-squared value for the model
          lm1.rsquared

Out[232]: 0.9907773400504103
```

```
In [238]: # create a fitted model with all three features
          lm2 = smf.ols(formula='price1 ~ price2 + price98 + price99', data=sml).fit()

          # print the coefficients
          lm2.params

Out[238]: Intercept   -18.816983
          price2        0.440564
          price98       0.169263
          price99       0.444685
          dtype: float64
```

Price for rent seem to have decreased by $18.82 when evaluated againts price2, 98, and 99.

Model creation

Adding 3 more models to do our evaluation which includes price1(2001) and price2(2002). Model2 includes price98(1998) and price99(1999) as well as model 3 which includes price1, price2, price98, price99, and price00(2000) .

```
In [113]: # Next we'll want to fit a linear regression model. We need to choose variables that we think we'll be good predictors for the d
          # This can be done by checking the correlation(s) between variables, on what variables are good predictors of y.

          import statsmodels.api as sm
          X = sml["price1"]
          y = sml["price2"]

          # Note the difference in argument order
          model = sm.OLS(y, X).fit()
          predictions = model.predict(X) # make the predictions by the model
```

```
In [116]: # # Next we'll want to fit a linear regression model by adding a constant.
          X = sml["price98"] ## X usually means our input variables (or independent variables)
          y = sml["price99"] ## Y usually means our output/dependent variable
          X = sm.add_constant(X) ## let's add an intercept (beta_0) to our model

          # Note the difference in argument order
          model2 = sm.OLS(y, X).fit() ## sm.OLS(output, input)
          predictions = model2.predict(X)
```

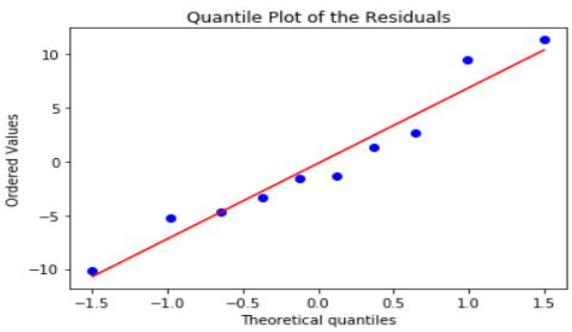
```
In [125]: # set input and output variables to use in regression model
          x = sml[['price2', 'price98', 'price99','price00']]
          y = sml['price1']

          # add intercept to input variable
          x = sm.add_constant(x)

          # fit regression model, using statsmodels GLM uses a different method but gives the same results
          #model = sm.GLM(y, x, family=sm.families.Gaussian()).fit()
          model3 = sm.OLS(y, x).fit()
```

Quantile residual plots for all 3 models

Quantile regression models is the relation between a set of predictor variables and specific percentiles or quantiles of the response variable. It specifies changes in the quantiles of the response. Quantile regression makes no assumptions about the distribution of the residuals.

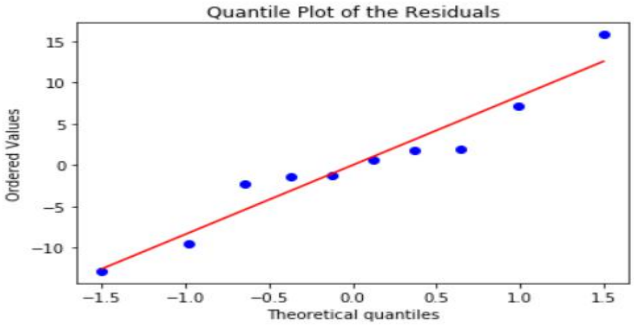
Plotting Model1

```
In [136]: import pylab
          # quantile plot of residuals
          stats.probplot(model.resid, plot=pylab)
          _ = plt.title('Quantile Plot of the Residuals');
```



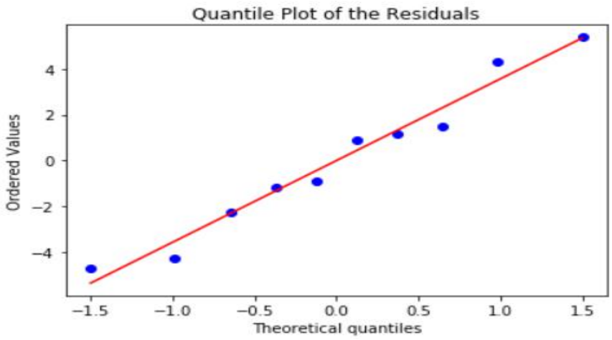
Plotting Model2

In [137]:
```
# quantile plot of residuals
stats.probplot(model2.resid, plot=pylab)
_ = plt.title('Quantile Plot of the Residuals');
```



Plotting Model3

In [138]:
```
import pylab
# quantile plot of residuals
stats.probplot(model3.resid, plot=pylab)
_ = plt.title('Quantile Plot of the Residuals');
```

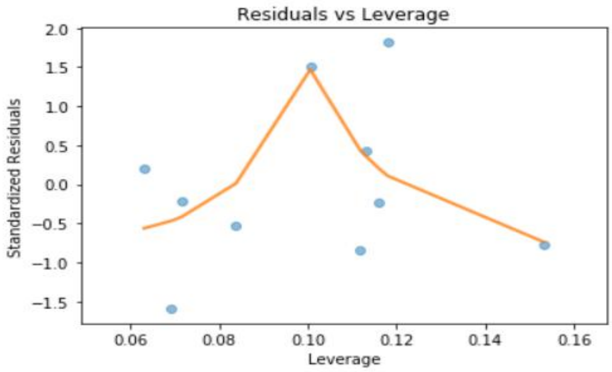


From the quantile plots above all 3 plots are close to perfect but model3 seem to be the most fitted plot.

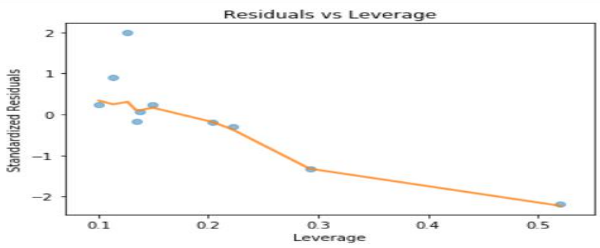
Normalizing the residuals for the models

The standardized residual is a measure of the strength of the difference between observed and expected values. It’s a measure of how significant your cells are to the chi-square value. When you compare the cells, the standardized residual makes it easy to see which cells are contributing the most to the value, and which are contributing the least.

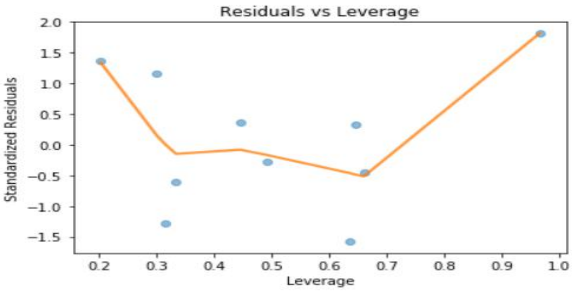
In [142]:
```
# normalized residuals
model_norm_residuals = model.get_influence().resid_studentized_internal
# leverage, from statsmodels internals
model_leverage = model.get_influence().hat_matrix_diag
plt.scatter(model_leverage, model_norm_residuals, alpha=0.5)
sns.regplot(model_leverage, model_norm_residuals,
            scatter=False,
            ci=False,
            lowess=True,
            line_kws={'color': 'C1', 'alpha': 0.8})
_ = plt.title('Residuals vs Leverage')
_ = plt.xlabel('Leverage')
_ = plt.ylabel('Standardized Residuals');
```



In [143]:
```
# normalized residuals
model_norm_residuals = model2.get_influence().resid_studentized_internal

# leverage, from statsmodels internals
model_leverage = model2.get_influence().hat_matrix_diag

plt.scatter(model_leverage, model_norm_residuals, alpha=0.5)
sns.regplot(model_leverage, model_norm_residuals,
            scatter=False,
            ci=False,
            lowess=True,
            line_kws={'color': 'C1', 'alpha': 0.8})

_ = plt.title('Residuals vs Leverage')
_ = plt.xlabel('Leverage')
_ = plt.ylabel('Standardized Residuals');
```



```
In [139]: # normalized residuals
          model_norm_residuals = model3.get_influence().resid_studentized_internal
          # leverage, from statsmodels internals
          model_leverage = model3.get_influence().hat_matrix_diag
          plt.scatter(model_leverage, model_norm_residuals, alpha=0.5)
          sns.regplot(model_leverage, model_norm_residuals,
                      scatter=False,
                      ci=False,
                      lowess=True,
                      line_kws={'color': 'C1', 'alpha': 0.8})
          _ = plt.title('Residuals vs Leverage')
          _ = plt.xlabel('Leverage')
          _ = plt.ylabel('Standardized Residuals');
```

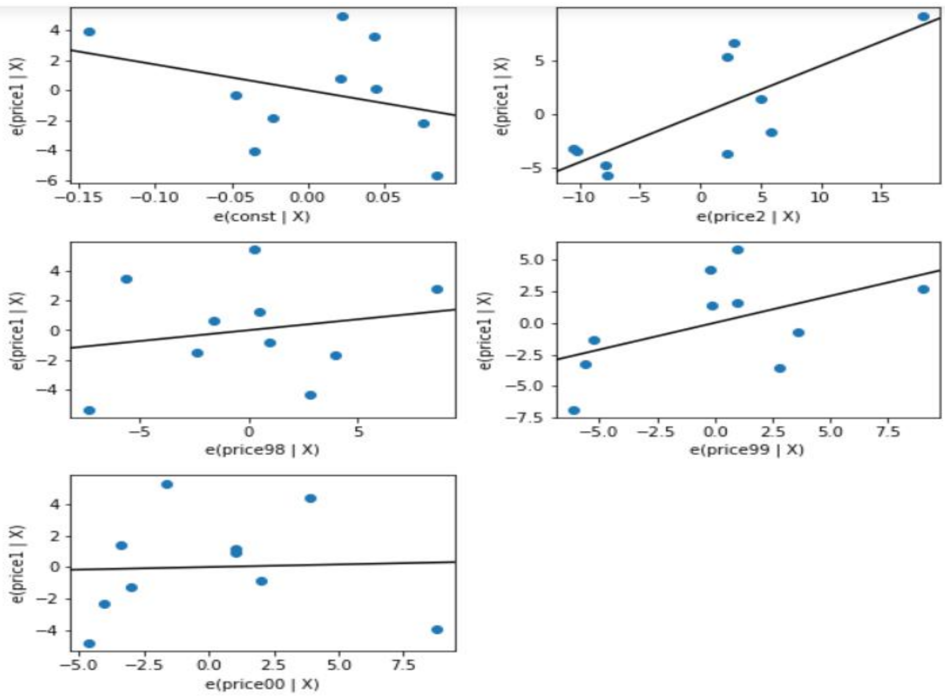


If the residual is less than -2, the cell's observed frequency is less than the expected frequency. Greater than 2 and the observed frequency is greater than the expected frequency.

Model3 Partial Regression Variable plots

Partial regression plots attempt to show the effect of adding an additional variable to the model given that one or more independent variables are already in the model. Partial regression plots are formed by:

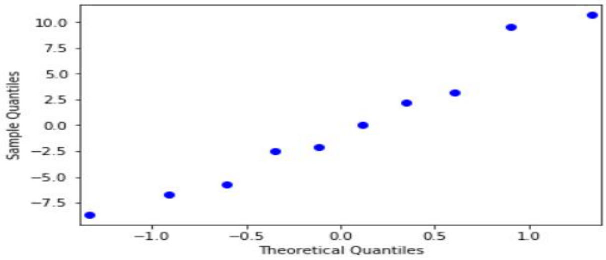
```
In [126]: # model3 variable plots
          fig = plt.figure(figsize=(8,8))
          fig = sm.graphics.plot_partregress_grid(model3, fig=fig)
```



QQ Plots

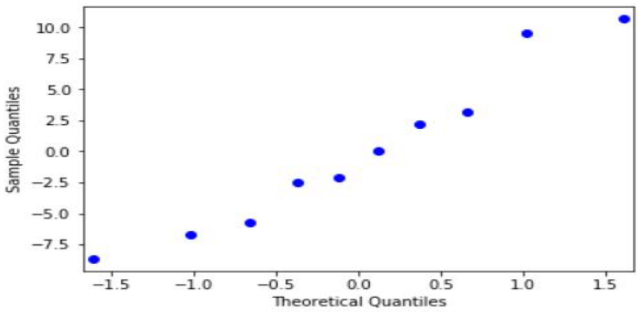
The Q-Q plot, or quantile-quantile plot, is a graphical tool to help us assess if a set of data plausibly came from some theoretical distribution such as a Normal or exponential. For example, if we run a statistical analysis that assumes our dependent variable is Normally distributed, we can use a Normal Q-Q plot to check that assumption. It's just a visual check, not an air-tight proof, so it is somewhat subjective. But it allows us to see at-a-glance if our assumption is plausible, and if not, how the assumption is violated and what data points contribute to the violation.

```
In [75]: # QQ Plots
         import statsmodels.api as sm
         from matplotlib import pyplot as plt
         res = model.resid # residuals
         fig = sm.qqplot(res)
         plt.show()
```



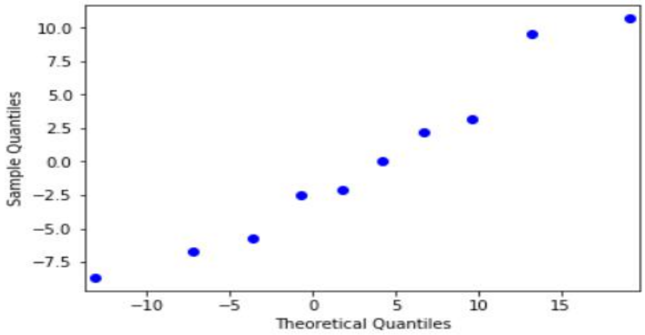
Qq plot of the residuals against quantiles of t-distribution with 4 degrees of freedom

```
In [76]: import scipy.stats as stats
         fig = sm.qqplot(res, stats.t, distargs=(4,))
         plt.show()
```



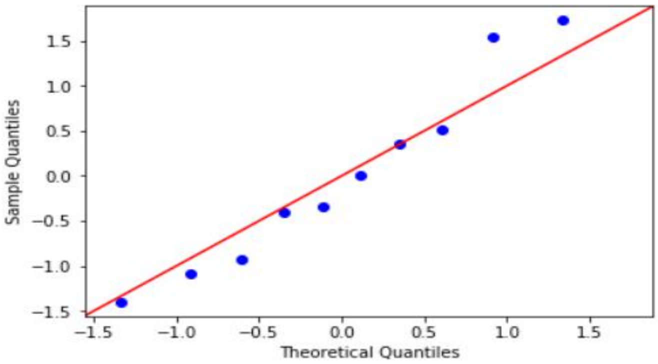
Qqplot against same as above, but with mean 3 and std 10

```
In [77]: fig = sm.qqplot(res, stats.t, distargs=(4,), loc=3, scale=10)
         plt.show()
```



Automatically determine parameters for t distribution including the loc and scale:

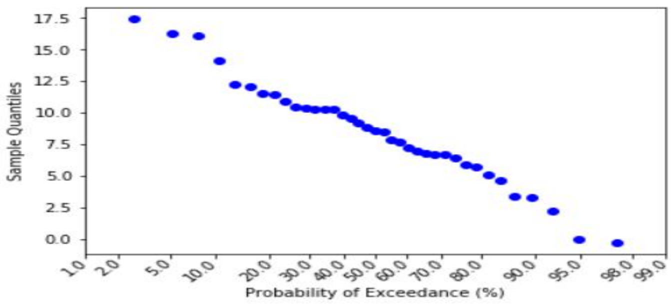
```
In [78]: fig = sm.qqplot(res, stats.t, fit=True, line='45')
         plt.show()
```

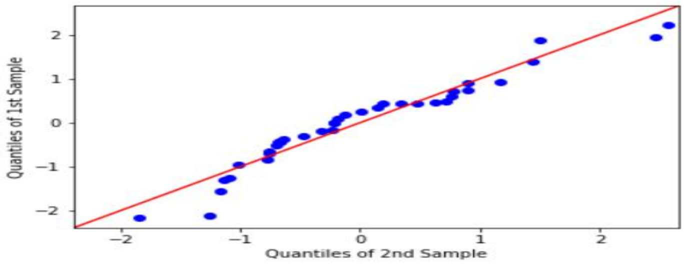


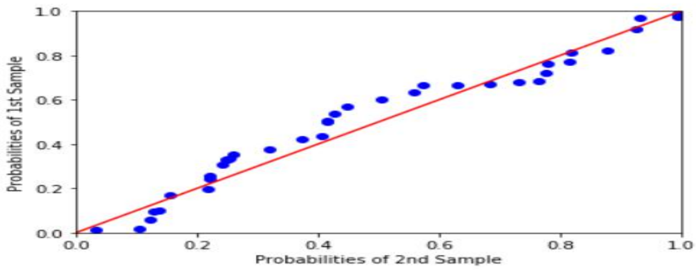
Probability Class

Randomly generate data from a standard Normal distribution and then find the quantiles.

```
In [79]: # ProbPlot class
         x = np.random.normal(loc=8.25, scale=3.5, size=37)
         y = np.random.normal(loc=8.00, scale=3.25, size=37)
         pp_x = sm.ProbPlot(x, fit=True)
         pp_y = sm.ProbPlot(y, fit=True)

         # probability of exceedance
         fig2 = pp_x.probplot(exceed=True)

         # compare x quantiles to y quantiles
         fig3 = pp_x.qqplot(other=pp_y, line='45')

         # same as above with probabilities/percentiles
         fig4 = pp_x.ppplot(other=pp_y, line='45')
```





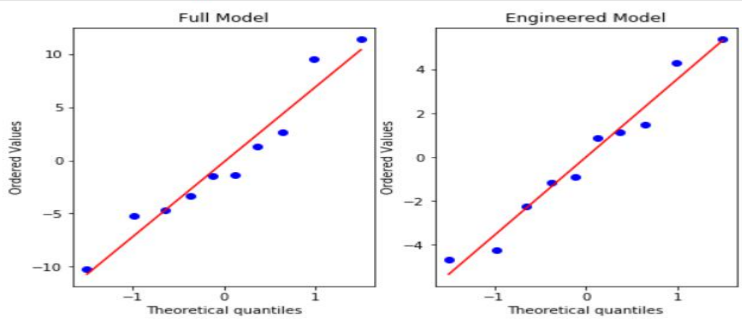


The results above is from the qq plot line 45

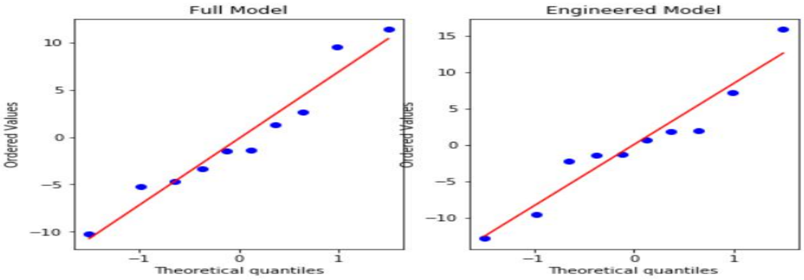
Probability Plots using all 3 models

Generates a probability plot of sample data against the quantiles of a specified theoretical distribution the normal distribution by default. probplot optionally calculates a best-fit line for the data and plots the results.

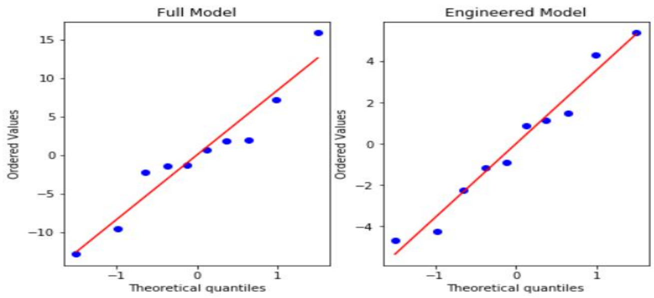
```
In [150]: plt.figure(figsize=(8, 5))

          plt.subplot(1, 2, 1)
          stats.probplot(model.resid, plot=pylab)
          _ = plt.title('Full Model');

          plt.subplot(1, 2, 2)
          stats.probplot(model3.resid, plot=pylab)
          _ = plt.title('Engineered Model');
```



```
In [151]: plt.figure(figsize=(8, 5))

          plt.subplot(1, 2, 1)
          stats.probplot(model.resid, plot=pylab)
          _ = plt.title('Full Model');

          plt.subplot(1, 2, 2)
          stats.probplot(model2.resid, plot=pylab)
          _ = plt.title('Engineered Model');
```




```
In [152]: plt.figure(figsize=(8, 5))

          plt.subplot(1, 2, 1)
          stats.probplot(model2.resid, plot=pylab)
          _ = plt.title('Full Model');

          plt.subplot(1, 2, 2)
          stats.probplot(model3.resid, plot=pylab)
          _ = plt.title('Engineered Model');
```



Handling Categorical Features

My goal to handel the categorical data was to be able to evaluate the cities, but when indexing there are only 2 categories which is 0 and 1. The error was spotted after creating the code because the dataset we are evaluating has 10 different cities it’s challenging to evaluate the cities using indexing.

```
In [278]: # set a seed for reproducibility
          np.random.seed(12345)

          # create a Series of booleans in which roughly half are True
          nums = np.random.rand(len(sml))
          mask_large = nums > 0.5

          # initially set Size to small, then change roughly half to be large
          sml['City'] = 'Brantford'

          # set a seed for reproducibility

          # Series.loc is a purely label-location based indexer for selection by label
          sml.loc[mask_large, 'City'] = 'Sherbrooke'
          sml.loc[mask_large, 'City'] = 'Trois-Rivi•res'
          sml.loc[mask_large, 'City'] = 'Saint John'
          sml.loc[mask_large, 'City'] = 'Saguenay'
          sml.loc[mask_large, 'City'] = 'Saskatoon'
          sml.loc[mask_large, 'City'] = 'Moncton'
          sml.loc[mask_large, 'City'] = 'Regina'
          sml.loc[mask_large, 'City'] = 'Montral'
          sml.loc[mask_large, 'City'] = 'Gatineau'

          sml.head()
```

Out[278]:

	City	1992	1993	1994	1995	1996	1997	price98	price99	price00	...	2007	2008	2009	2010	2011	2012	2013	2014	2015	price16
6	Gatineau	395.0	400.0	402.0	406.0	405.0	406.0	411.0	403.0	413.0	...	487.0	505.0	520.0	533.0	547.0	550.0	555.0	568.0	581.0	587.0
5	Brantford	408.0	418.0	420.0	422.0	426.0	426.0	433.0	434.0	437.0	...	529.0	543.0	553.0	566.0	577.0	578.0	591.0	604.0	608.0	622.0
4	Brantford	420.0	419.0	416.0	417.0	423.0	425.0	428.0	428.0	438.0	...	490.0	518.0	518.0	535.0	557.0	549.0	571.0	595.0	598.0	587.0

In [279]:
```
# create three dummy variables using get_dummies
pd.get_dummies(sml.City, prefix='City').head()
```

Out[279]:

	City_Brantford	City_Gatineau
6	0	1
5	1	0
4	1	0
3	1	0
26	0	1

Model Summary

OLS stands for Ordinary Least Squares and the method “Least Squares” means that we’re trying to fit a regression line that would minimize the square of distance from the regression line.

Model1

In [281]:
```
print(model.summary())
                            OLS Regression Results
==============================================================================
Dep. Variable:                 price1   R-squared:                       0.993
Model:                            OLS   Adj. R-squared:                  0.992
Method:                 Least Squares   F-statistic:                     1124.
Date:                Fri, 30 Aug 2019   Prob (F-statistic):           6.84e-10
Time:                        00:19:32   Log-Likelihood:                -31.966
No. Observations:                  10   AIC:                             67.93
Df Residuals:                       8   BIC:                             68.54
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     12.1919     15.376      0.793      0.451     -23.265      47.648
price2         0.9526      0.028     33.527      0.000       0.887       1.018
==============================================================================
Omnibus:                        0.836   Durbin-Watson:                   1.765
Prob(Omnibus):                  0.658   Jarque-Bera (JB):                0.677
Skew:                          -0.341   Prob(JB):                        0.713
Kurtosis:                       1.923   Cond. No.                     3.98e+03
==============================================================================
```

Model2

In [194]:
```
print(model2.summary())
                            OLS Regression Results
==============================================================================
Dep. Variable:                price99   R-squared:                       0.985
Model:                            OLS   Adj. R-squared:                  0.984
Method:                 Least Squares   F-statistic:                     540.3
Date:                Thu, 29 Aug 2019   Prob (F-statistic):           1.25e-08
Time:                        13:43:37   Log-Likelihood:                -34.456
No. Observations:                  10   AIC:                             72.91
Df Residuals:                       8   BIC:                             73.52
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        -15.1279     22.280     -0.679      0.516     -66.506      36.251
price98        1.0405      0.045     23.245      0.000       0.937       1.144
==============================================================================
Omnibus:                        1.181   Durbin-Watson:                   1.262
Prob(Omnibus):                  0.554   Jarque-Bera (JB):                0.160
Skew:                           0.309   Prob(JB):                        0.923
Kurtosis:                       3.064   Cond. No.                     4.13e+03
==============================================================================
```

Model3

```
In [195]: print(model3.summary())
                            OLS Regression Results
==============================================================================
Dep. Variable:                 price1   R-squared:                       0.998
Model:                            OLS   Adj. R-squared:                  0.996
Method:                 Least Squares   F-statistic:                     623.7
Date:                Thu, 29 Aug 2019   Prob (F-statistic):           6.25e-07
Time:                        13:48:34   Log-Likelihood:                -25.656
No. Observations:                  10   AIC:                             61.31
Df Residuals:                       5   BIC:                             62.82
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        -17.2774     21.621     -0.799      0.460     -72.857      38.302
price2         0.4473      0.162      2.759      0.040       0.030       0.864
price98        0.1458      0.320      0.455      0.668      -0.677       0.969
price99        0.4239      0.315      1.344      0.237      -0.387       1.235
price00        0.0330      0.353      0.094      0.929      -0.873       0.940
==============================================================================
Omnibus:                        0.248   Durbin-Watson:                   1.603
Prob(Omnibus):                  0.883   Jarque-Bera (JB):                0.403
Skew:                           0.157   Prob(JB):                        0.818
Kurtosis:                       2.068   Cond. No.                     1.58e+04
==============================================================================
```

Model Interpretation

Omnibus/Prob(Omnibus) is a test of the skewness and kurtosis of the residual. We hope to see a value close to zero which would indicate normalcy. The Prob (Omnibus) performs a statistical test indicating the probability that the residuals are normally distributed. We hope to see something close to 1 here. In this case Omnibus is relatively low and the Prob (Omnibus) is relatively high so the data is somewhat normal.

Skew is a measure of data symmetry. We want to see something close to zero, indicating the residual distribution is normal. This value also drives the Omnibus. This result has a small, and therefore good, skew.

Kurtosis is a measure of "peakiness", or curvature of the data. Higher peaks lead to greater Kurtosis. Greater Kurtosis can be interpreted as a tighter clustering of residuals around zero, implying a better model with few outliers.

Durbin-Watson tests for homoscedasticity characteristic . We hope to have a value between 1 and 2. In this case, the data is close, but within limits.

Jarque-Bera (JB)/Prob(JB) like the Omnibus test in that it tests both skew and kurtosis. We hope to see in this test a confirmation of the Omnibus test. In this case we do.

Condition Number This test measures the sensitivity of a function's output as compared to its input . When we have multicollinearity, we can expect much higher fluctuations to small changes in the data, hence, we hope to see a relatively small number, something below 30. In this case we are well below 30.

In looking at the data we see an okay though not great set of characteristics. This would indicate that the OLS approach has some validity, but we can probably do better with a nonlinear model.

Model1 Accuracy

```
In [38]: from sklearn.dummy import DummyRegressor
         from sklearn.metrics import mean_absolute_error
         from sklearn.metrics import r2_score
         from sklearn.model_selection import train_test_split
         y = price1
         X = price2
         X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2,random_state=100)
         dummy_median = DummyRegressor(strategy='mean')
         dummy_regressor = dummy_median.fit(X_train,y_train)
         dummy_predicts = dummy_regressor.predict(X_test)
         print("Model Accuracy:", dummy_regressor.score(X_test,y_test)*100)

         Model Accuracy: -565.585963182117
```

Model Selection

We have decided to use model3 as our final model as our final model. The reason is because model3 is making it's predictions working against several other variables.

Loading in the income dataset

```
In [20]: # Loading the income after tax dataset
         income= pd.read_csv(r"C:\\Users\\susie\\Documents\\Data Science\\Capstone data\\Average after tax income.csv"
                             ,encoding="latin1")
```

The income dataset is very similar to the rent dataset most of the same steps will be repeated to evaluate the income dataset that was used previously to evaluate the ren dataset. To avoid repetition we wont be explaining the outputs if they have already been explained previously.

Looking at the head of the dataset

```
In [21]: income.head(5)
Out[21]:
```

	Cities	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
0	Canada	42500	43800	45500	45400	45000	44800	45800	46700	48000	48200	49100	50300
1	Newfoundland and Labrador	37300	37400	38800	37400	39000	43100	42000	44400	45600	44000	45700	40200
2	Prince Edward Island	36500	38900	42400	42900	41200	38200	38400	40000	37200	42300	44900	43100
3	Nova Scotia	37400	40300	38200	38800	39600	42400	40800	42700	41200	41400	43000	43000
4	New Brunswick	36300	37100	38600	38100	41500	37000	36000	38900	38100	37900	38400	38200

```
In [22]: income.columns
```

The income dataset is also made up of mostly numeric variable only one column has objects.

Income dataset columns

In [93]:
```
income.columns
```

Out[93]:
```
Index(['Cities', '2006', '2007', '2008', '2009', '2010', '2011', '2012',
       '2013', '2014', '2015', '2016', '2017'],
      dtype='object')
```

The dataset has 29 rows and 13 columns

Checking for missing data

In [89]:
```
# The df.info() method is great for seeing all the c
print(income.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29 entries, 0 to 28
Data columns (total 13 columns):
Cities     29 non-null object
2006       29 non-null int64
2007       29 non-null int64
2008       29 non-null int64
2009       29 non-null int64
2010       29 non-null int64
2011       29 non-null int64
2012       29 non-null int64
2013       29 non-null int64
2014       29 non-null int64
2015       29 non-null int64
2016       29 non-null int64
2017       29 non-null int64
dtypes: int64(12), object(1)
memory usage: 3.0+ KB
None
```

There are no missing values in the income data

Finding the cities with the lowest and highest income bracket

Top 10 cities with the highest income bracket

Finding the hightest and lowest income ranges for top 10 cities.

For the income dataset we will be forcusing on the the cities with the highest income bracket

In [ ]:
```
# Filtering the data to find the cities with the lowest income
```

In [24]:
```
# Using the n.smallest I will search the data to find cities with the highest income.
low = income.nsmallest(10, ['2006', '2007', '2008', '2009', '2010', '2011', '2012',
      '2013', '2014', '2015', '2016', '2017'])
low
```

Out[24]:

	Cities	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
17	Trois-Rivières	28700	36800	35800	36500	34800	34300	31300	34100	33600	31800	38500	36200
14	Saguenay	31600	33100	33800	34100	35400	38400	37000	38200	33000	35400	37800	35100
16	Sherbrooke	32900	34800	36100	35400	36600	34100	32600	35300	36200	41500	37700	35800
11	St John's	34400	33000	38000	38300	40000	42300	42900	48400	49500	48300	45700	43400
33	Regina	36000	44000	43700	44100	53400	51600	53300	53900	57600	53700	54600	53400
4	New Brunswick	36300	37100	38600	38100	41500	37000	36000	38900	38100	37900	38400	38200
2	Prince Edward Island	36500	38900	42400	42900	41200	38200	38400	40000	37200	42300	44900	43100
7	Manitoba	36800	40000	38600	38000	39200	43600	41900	43700	45200	44100	45500	44400
31	Thunder Bay	37100	38900	35000	39400	42800	36800	40500	39000	38800	45500	42800	44800
32	Winnipeg	37200	40400	38100	37600	39300	42900	42100	42800	43700	42400	44600	43700

In [ ]:
```
# Filtering the data to find the cities with the lowest income
```

Top 10 cities with the highest income brackets

```
In [23]: # Using the n.largest I will search the data to find cities with the highest income.
high = income.nlargest(10, ['2006', '2007', '2008', '2009', '2010', '2011', '2012',
        '2013', '2014', '2015', '2016', '2017'])
high
```

Out[23]:

	Cities	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
35	Calgary	58000	65800	71000	61800	61700	63200	67300	70000	66500	63900	63400	66700
9	Alberta	54400	59800	62200	63300	62200	60000	64700	66000	67500	68600	64200	65400
36	Edmonton	50100	58400	56900	66800	65800	58600	57900	61800	67800	72200	66800	66200
37	Abbotsford	49200	44000	42100	47700	42500	47000	53100	44900	55300	46800	55400	53900
39	Victoria	47400	47300	47200	45300	38900	52900	45300	47000	45400	42700	54500	54900
38	Vancouver	46600	50600	47800	45800	49000	47300	54000	51100	51300	53000	54200	59300
10	British Columbia	46600	48400	48500	46000	46700	47900	50900	49600	49700	49500	53000	57700
21	Ottawa - Gatineau (Québec)	46400	44800	42100	42200	38600	46600	37100	41800	37600	44400	44600	44200
27	Kitchener	45800	50800	46100	50800	42900	45100	40200	49800	46300	54000	54000	55800
24	Toronto	45600	45700	50200	51900	51100	46200	47900	49200	53300	55500	55900	59800

For this dataset will be focusing on the cities with the highest income brackets. Usually cities with the highest income bracket would also have higher housing costs, but there are also other factors that affects the cost of living. The top 10 cities with the highest income brackets are Calgary, Alberta, Edmonton, Abbotsford, Victoria, British Columbia, Ottawa, Kitchener and Toronto.

Plotting a heat map to find the most correlated years

```
f,ax = plt.subplots(figsize=(9,8))
sns.heatmap(high.corr(), annot = True,linewidths=.4, fmt='.1f', ax=ax)
plt.show()
```

In the correlation heatmap it seems as though 2013, 2010,2007, 2008and 2017 have the strongest correlation.

Renaming the columns

```
In [183]: #Renaming 2013 column name
          high.rename(columns={'2013': 'income13'}, inplace=True)
```

```
In [184]: #Renaming 2015 column name
          high.rename(columns={'2008': 'income8'}, inplace=True)
```

```
In [185]: #Renaming 2009 column name
          high.rename(columns={'2007': 'income7'}, inplace=True)
```

```
In [187]: #Renaming 2009 column name
          high.rename(columns={'2010': 'income10'}, inplace=True)
```

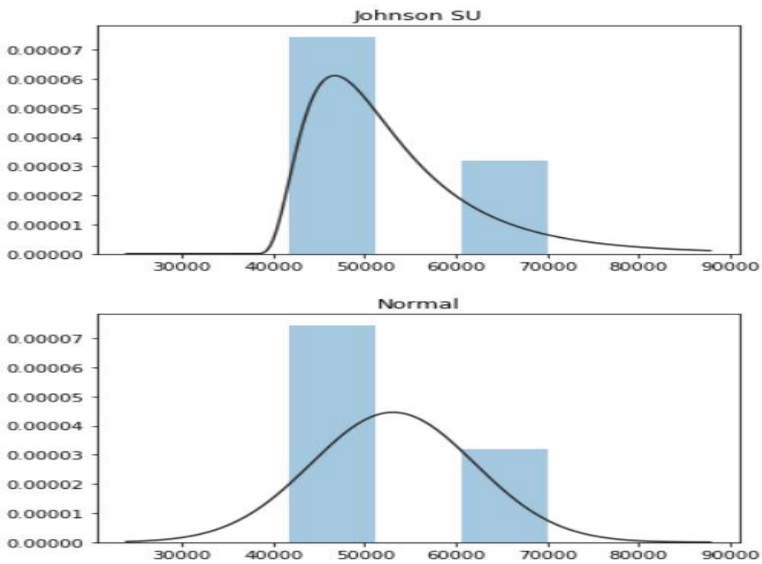
```
In [192]: #Renaming 2009 column name
          high.rename(columns={'2017': 'income17'}, inplace=True)
```

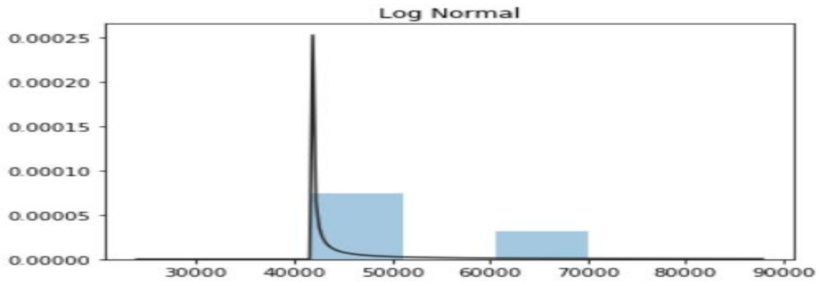
These variables are much easier to work with if they are renamed, because the column names were numbers, we might run into issues later if they aren't renamed before hand.

Johnson SU distribution plot

The mu and sigma are the mean and the standard deviation of the distribution. The Johnson plot is a transformation of the normal distribution the Johnson SU was developed to in order to apply the established methods and theory of the normal distribution to non-normal datasets.

```
In [45]: # Johnson Su distribution plot for 2005

         import scipy.stats as st
         y = high[['income13']]
         plt.figure(1); plt.title('Johnson SU')
         sns.distplot(y, kde=False, fit=st.johnsonsu)
         plt.figure(2); plt.title('Normal')
         sns.distplot(y, kde=False, fit=st.norm)
         plt.figure(3); plt.title('Log Normal')
         sns.distplot(y, kde=False, fit=st.lognorm)

Out[45]: <matplotlib.axes._subplots.AxesSubplot at 0x225508099b0>
```

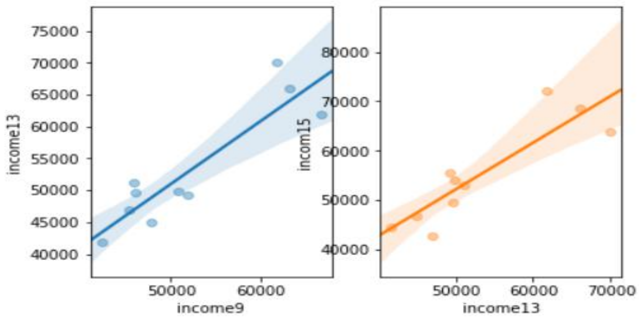




Regression Plot

The line of best fit is calculated by minimizing the ordinary least squares error function, that Seaborn module does automatically using the regplot function. The shaded area around the line represents 95% confidence intervals. When running a regression, statwing automatically calculates and plots residuals to help understand and improve the regression model.

```
In [47]: # Regression plot
         fig, ax = plt.subplots(1,2)
         sns.regplot('income9','income13',high, ax=ax[0], scatter_kws={'alpha':0.4})
         sns.regplot('income13','incom15',high,ax=ax[1], scatter_kws={'alpha':0.4})

Out[47]: <matplotlib.axes._subplots.AxesSubplot at 0x22551a04550>
```

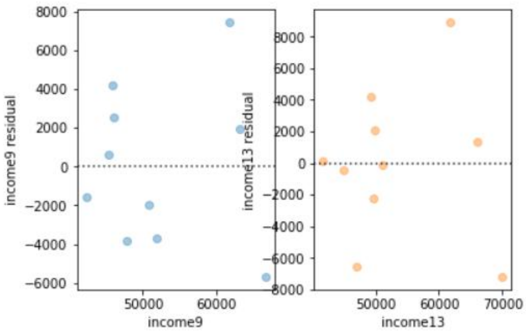


Residual Plot

The points in the residual plot represent the difference between the sample (y) and the predicted value (y’). Residuals that are greater than zero are points that are underestimated by the model and residuals less than zero are points that are overestimated by the model.

In [48]:
```
# visualizing the residuals by creating residual plots .
fig, ax = plt.subplots(1,2)
ax[0]= sns.residplot('income9','income13', high,ax=ax[0], scatter_kws={'alpha':0.4})
ax[0].set_ylabel('income9 residual')
ax[1]=sns.residplot('income13','incom15',high,ax=ax[1], scatter_kws={'alpha':0.4})
ax[1].set_ylabel('income13 residual')
```

Out[48]: `Text(0, 0.5, 'income13 residual')`



Model Creation

Creating a fitted linear model

In [288]:
```
# # Next we'll want to fit a linear model.Create a fitted model.
import statsmodels.formula.api as smf
lm3 = smf.ols(formula='income8 ~ income10', data=high).fit()

# print the coefficients
lm3.params
```

Out[288]:
```
Intercept     12608.045755
income10          0.770826
dtype: float64
```

```
Income seem to have increased by $77.08 from 2008 to 2010
```

Income seem to have increased by $77.08 from 2008 to 2010

P Values

In [290]:
```
# The P valus represents the probability that the coefficient is actually zero
#print the p-values for the model coefficients
lm3.pvalues
```

Out[290]:
```
Intercept    0.206636
income10     0.003098
dtype: float64
```

P values represents the probability that the coefficient is actually zero.

R Square

In [289]:
```
# print the R-squared value for the model
lm3.rsquared
```

Out[289]: `0.6854910493220028`

```
In [291]: # create a fitted model with all three features
          lm4 = smf.ols(formula='income7 ~ income8 + income10 + income17', data=high).fit()

          # print the coefficients
          lm4.params

Out[291]: Intercept    9418.317847
          income8         0.635990
          income10        0.033458
          income17        0.130803
          dtype: float64
```

Model Summary

OLS stands for Ordinary Least Squares and the method "Least Squares" means that we're trying to fit a regression line that would minimize the square of distance from the regression line.

Lm3

```
In [293]: # Print out the statistics
          print(lm3.summary())

                            OLS Regression Results
==============================================================================
Dep. Variable:                income8   R-squared:                       0.685
Model:                            OLS   Adj. R-squared:                  0.646
Method:                 Least Squares   F-statistic:                     17.44
Date:                Fri, 30 Aug 2019   Prob (F-statistic):            0.00310
Time:                        14:07:14   Log-Likelihood:                -98.292
No. Observations:                  10   AIC:                             200.6
Df Residuals:                       8   BIC:                             201.2
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept   1.261e+04   9174.635      1.374      0.207   -8548.700    3.38e+04
income10       0.7708      0.185      4.176      0.003       0.345       1.197
==============================================================================
Omnibus:                        6.807   Durbin-Watson:                   2.147
Prob(Omnibus):                  0.033   Jarque-Bera (JB):                2.586
Skew:                           1.152   Prob(JB):                        0.274
Kurtosis:                       3.950   Cond. No.                     2.87e+05
==============================================================================
```

LM4

```
In [294]: print(lm4.summary())

                            OLS Regression Results
==============================================================================
Dep. Variable:                income7   R-squared:                       0.880
Model:                            OLS   Adj. R-squared:                  0.821
Method:                 Least Squares   F-statistic:                     14.72
Date:                Fri, 30 Aug 2019   Prob (F-statistic):            0.00357
Time:                        14:22:58   Log-Likelihood:                -91.244
No. Observations:                  10   AIC:                             190.5
Df Residuals:                       6   BIC:                             191.7
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept   9418.3178   8509.815      1.107      0.311   -1.14e+04    3.02e+04
income8        0.6360      0.211      3.020      0.023       0.121       1.151
income10       0.0335      0.224      0.150      0.886      -0.514       0.580
income17       0.1308      0.268      0.487      0.643      -0.526       0.788
==============================================================================
Omnibus:                        4.123   Durbin-Watson:                   2.173
Prob(Omnibus):                  0.127   Jarque-Bera (JB):                1.301
Skew:                          -0.836   Prob(JB):                        0.522
Kurtosis:                       3.570   Cond. No.                     8.54e+05
==============================================================================
```

The statistics in the last table are testing the normality of our data. If the Prob(Omnibus) is very small, and I took this to mean <.05 as this is standard statistical practice, then our data is probably not normal. This is a more precise way than graphing our data to determine if our data is normal.

Statsmodels also helps us determine which of our variables are statistically significant through the p-values. If our p-value is <.05, then that variable is statistically significant. This is a useful tool to tune your model. In the case of the iris data set we can put in all of our variables to determine which would be the best predictor.

Model Interpretation

Omnibus/Prob(Omnibus) is a test of the skewness and kurtosis of the residual. We hope to see a value close to zero which would indicate normalcy. The Prob (Omnibus) performs a statistical test indicating the probability that the residuals are normally distributed. We hope to see something close to 1 here. In this case Omnibus is relatively low and the Prob (Omnibus) is relatively high so the data is somewhat normal.

Skew is a measure of data symmetry. We want to see something close to zero, indicating the residual distribution is normal. This value also drives the Omnibus. This result has a small, and therefore good, skew.

Kurtosis is a measure of "peakiness", or curvature of the data. Higher peaks lead to greater Kurtosis. Greater Kurtosis can be interpreted as a tighter clustering of residuals around zero, implying a better model with few outliers.

Durbin-Watson tests for homoscedasticity characteristic . We hope to have a value between 1 and 2. In this case, the data is close, but within limits.

Jarque-Bera (JB)/Prob(JB) like the Omnibus test in that it tests both skew and kurtosis. We hope to see in this test a confirmation of the Omnibus test. In this case we do.

Condition Number This test measures the sensitivity of a function's output as compared to its input . When we have multicollinearity, we can expect much higher fluctuations to small changes in the data, hence, we hope to see a relatively small number, something below 30. In this case we are well below 30.

In looking at the data we see an okay though not great set of characteristics. This would indicate that the OLS approach has some validity, but we can probably do better with a nonlinear model.

Loading the market indicator dataset

In [51]:
```
# Loading the monthly debt payments
market= pd.read_csv(r"C:\\Users\\susie\\Documents\\Data Science\\Capstone data\\Housing market indicators.csv"
                  ,encoding="latin1")
```

In [52]:
```
market.head(5)
```

Out[52]:

	Indicators	1990	1991	1992	1993	1994	1995	1996	1997	1998	...	2007	2008	2009	2010	2011	2012	20
0	Single-detached	32425.0	26290.0	27868.0	26240.0	30036.0	20124.0	27019.0	35401.0	32737.0	...	37910.0	31108.0	22634.0	28089.0	26884.0	25567.0	23270
1	Multiple	30224.0	26504.0	27904.0	18900.0	16609.0	15694.0	16043.0	18671.0	21093.0	...	30213.0	43968.0	27736.0	32344.0	40937.0	51175.0	37815
2	Semi-detached	2338.0	1730.0	2611.0	2537.0	3421.0	2306.0	3348.0	4299.0	4575.0	...	4284.0	3415.0	3007.0	3006.0	3142.0	3397.0	3116
3	Row	8462.0	9472.0	9246.0	7448.0	7226.0	6175.0	8124.0	9964.0	10073.0	...	11255.0	11212.0	7121.0	10255.0	9288.0	10577.0	9427
4	Apartment	19424.0	15302.0	16047.0	8915.0	5962.0	7213.0	4571.0	4408.0	6445.0	...	14674.0	29341.0	17608.0	19083.0	28507.0	37201.0	25272

5 rows × 28 columns

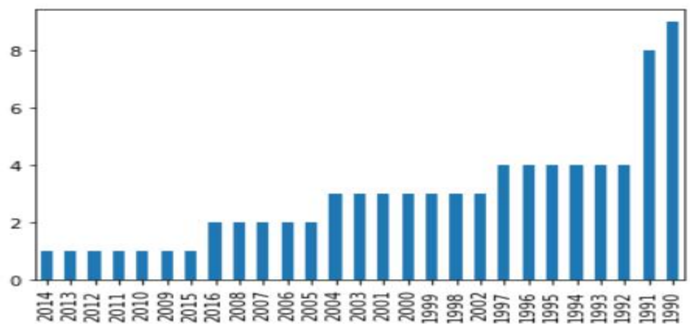
Missing values

```
In [27]: # We have to sure we set the data up in order
         # lets take a look at the null values
         print(market.isnull().sum().to_string())
```

```
Indicators     0
1990           9
1991           8
1992           4
1993           4
1994           4
1995           4
1996           4
1997           4
1998           3
1999           3
2000           3
2001           3
2002           3
2003           3
2004           3
2005           2
2006           2
2007           2
2008           2
2009           1
2010           1
2011           1
2012           1
2013           1
2014           1
2015           1
2016           2
```

Plotting the missing values

```
In [54]: # Here we have a visual of the missing data
         missing = market.isnull().sum()
         missing = missing[missing > 0]
         missing.sort_values(inplace=True)
         missing.plot.bar()

Out[54]: <matplotlib.axes._subplots.AxesSubplot at 0x22551b2f7b8>
```



Replacing missing values with NAN

```
In [104]: # Replacing missing values with NAN
          import numpy
          # mark zero values as missing or NaN
          dataset = market.replace(0, numpy.NaN)

In [105]: # print the first 20 rows of data
          print(market.head(20))
```

```
                                    Indicators      1990      1991  \
0                               Single-detached  32425.00  26290.00
1                                      Multiple  30224.00  26504.00
2                                 Semi-detached   2338.00   1730.00
3                                           Row   8462.00   9472.00
4                                     Apartment  19424.00  15302.00
5                 Starts by intended market total  53341.00  46123.00
6                      Homeownership freehold  28104.00  24813.00
7                                        Rental  12158.00  14519.00
8                   Homeownership  condominium  11435.00   4240.00
9                        Other co-op and unknown   1644.00   2551.00
10                            Completions total  80562.00  59622.00
11                 Residential Building Permits  61578.00  60093.00
12        Residential Building Permits  $ thousands   6302.92   6205.22
13               Newly completed and unabsorbed homes       NaN       NaN
14                      Single and semi-detached       NaN       NaN
15                           Row and apartment       NaN       NaN
16                         Rental vacancy rate %      1.40      2.20
17                    Rental availability rate %       NaN       NaN
18  Vacancy Rate Standard Spaces in Seniors Rental       NaN       NaN
19                New Housing Price Index % change     -1.33    -10.70
```

The top 10 highest market indicators

The market indicators are what drives cost of living

In [55]:
```python
# Using the n.largest I will search the data to find the top 10 indicators that affects houssing cost.
top = market.nlargest(10, ['1991', '1992', '1993', '1994', '1995', '1996',
       '1997', '1998', '1999', '2000', '2001', '2002', '2003', '2004', '2005',
       '2006', '2007', '2008', '2009', '2010', '2011', '2012', '2013', '2014',
       '2015', '2016'])
top
```

Out[55]:

	Indicators	1990	1991	1992	1993	1994	1995	1996	1997	1998	...	2007	2008	2009	
11	Residential Building Permits	61578.000	60093.000	54272.000	45480.000	49404.000	38610.000	46437.000	61070.000	59675.000	...	73271.000	70031.000	57653.000	68
10	Completions total	80562.000	59622.000	63134.000	51130.000	49106.000	36278.000	40729.000	51297.000	48403.000	...	64139.000	67737.000	54900.000	61
5	Starts by intended market total	53341.000	46123.000	48693.000	38847.000	41560.000	31893.000	39512.000	49972.000	50088.000	...	62775.000	71923.000	47939.000	57
1	Multiple	30224.000	26504.000	27904.000	18900.000	16609.000	15694.000	16043.000	18671.000	21093.000	...	30213.000	43968.000	27736.000	32
0	Single-detached	32425.000	26290.000	27868.000	26240.000	30036.000	20124.000	27019.000	35401.000	32737.000	...	37910.000	31108.000	22634.000	28
6	Homeownership freehold	28104.000	24813.000	27917.000	26332.000	32516.000	22685.000	31634.000	40925.000	39649.000	...	45626.000	38613.000	28460.000	35
4	Apartment	19424.000	15302.000	16047.000	8915.000	5962.000	7213.000	4571.000	4408.000	6445.000	...	14674.000	29341.000	17608.000	19
7	Rental	12158.000	14519.000	13798.000	7974.000	4148.000	2884.000	1289.000	790.000	1181.000	...	2994.000	3867.000	4811.000	3
29	Population on July 1 (thousands)	10295.832	10431.316	10572.205	10690.038	10819.146	10950.119	11082.903	11227.651	11365.901	...	12764.195	12882.625	12997.687	13
3	Row	8462.000	9472.000	9246.000	7448.000	7226.000	6175.000	8124.000	9964.000	10073.000	...	11255.000	11212.000	7121.000	10

The top 10 lowest market indicators

In [56]:
```python
# Using the n.smallest I will search the data to find the top 10 indicators that affects houssing cost.
low = market.nsmallest(10, ['1990','1991', '1992', '1993', '1994', '1995', '1996',
       '1997', '1998', '1999', '2000', '2001', '2002', '2003', '2004', '2005',
       '2006', '2007', '2008', '2009', '2010', '2011', '2012', '2013', '2014',
       '2015', '2016'])
low
```

Out[56]:

	Indicators	1990	1991	1992	1993	1994	1995	1996	1997	1998	...	2007	2008	
19	New Housing Price Index % change	-1.330000	-10.700000	-3.21000	-1.710000	-0.280000	-0.020000	-1.010000	2.080000	2.500000	...	2.620000	3.510000	
31	Employment (% change)	-0.093768	-3.409135	-1.67844	0.105078	1.531143	1.722633	1.291011	2.416188	3.084520	...	1.443405	0.989871	
16	Rental vacancy rate %	1.400000	2.200000	2.60000	2.700000	2.400000	2.300000	3.000000	2.800000	2.600000	...	3.300000	2.700000	
23	Rental accommodation costs % change	3.990000	3.420000	2.92000	2.590000	2.090000	1.740000	1.440000	1.490000	1.260000	...	0.980000	0.850000	
20	Consumer Price Index % change	4.820000	4.640000	1.02000	1.780000	0.050000	2.470000	1.520000	1.880000	0.930000	...	1.830000	2.270000	
32	Unemployment rate %	6.200000	9.500000	10.80000	10.900000	9.600000	8.700000	9.000000	8.400000	7.200000	...	6.400000	6.600000	
22	Owned accommodation costs % change	6.630000	2.110000	-0.43000	-0.840000	-1.390000	1.460000	-0.830000	-0.780000	0.400000	...	3.240000	3.640000	
30	Labour force participation rate %	69.541667	68.533333	67.35000	66.683333	65.916667	65.475000	65.541667	65.733333	65.933333	...	67.750000	67.716667	6
24	Bachelor	417.000000	443.000000	456.00000	470.000000	479.000000	490.000000	496.000000	507.000000	531.000000	...	668.000000	691.000000	68
25	One bedroom	508.000000	538.000000	557.00000	573.000000	586.000000	601.000000	609.000000	616.000000	645.000000	...	797.000000	820.000000	82

Insights

Abbotsford was the only city that appeared in 2 different search it appeared in the top 10 for the least expensive 2 bedroom rental price and in the top 10 in cities with the highest income bracket.

Conclusion

This dataset was very chanlenging to work with. Not only was the dataset small but the dataset didn’t have much variable options to work with. Year was being used againts year to do the evaluating which is not a realistic approach. This approach ended up giving all perfect plots for our modeling section. With the project being analysing rent prices it’s evident that the price will go up every year. To be able to have a more solid model we suggest using a much more stronger dataset that has more variable options to work with.