Final Project Submission

Please fill out:

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- Scheduled project review date/time: 30th October - 4th November 2023
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- Blog post URL:

BUSINESS UNDERSTANDING

The core of this project lies in gaining a profound understanding of the real estate market and providing valuable insights to various stakeholders. Let's delve into the business understanding aspect in relation to the project: Real Estate Market Analysis: Understanding the real estate market is essential for both buyers and sellers. By analyzing the data set, we aim to identify trends, factors, and patterns that influence housing prices. This knowledge can help potential buyers make informed decisions, assist sellers in setting competitive prices, and guide investors in identifying profitable opportunities. Investment Decision Support: Real estate is a significant investment for most individuals. Buyers, especially first-time home buyers, need insights into what features drive property prices. We aim to provide recommendations on where to invest based on the property's attributes, which could potentially save buyers money and time. Seller Strategies: For those selling properties, understanding the market and how specific features influence prices is crucial. By comprehending the impact of variables like condition, location, and grade, sellers can make informed decisions about property improvements and pricing strategies. Market Trends: As a real estate agent, investor, or market analyst, having access to market trends can be invaluable. Analyzing this data set can help in predicting future price changes and identifying areas with appreciating property values. Risk Management: For investors in the real estate market, understanding the relationship between property features and prices is vital for risk assessment. This analysis can contribute to more informed and profitable investment decisions.

DATA UNDERSTANDING

Effective data understanding is fundamental to deriving meaningful insights from the data set. In the context of this project, the data understanding phase involves the following aspects: Data Collection,Data Cleaning,Exploratory Data Analysis (EDA),Feature Selection,Data processing,Data Visualization and Data Quality Assurance

Variables

- `id` - Unique identifier for a house

- `id` - Unique identifier for a house
- `date` - Date house was sold
- `price` - Sale price (prediction target)
- `bedrooms` - Number of bedrooms
- `bathrooms` - Number of bathrooms
- `sqft_living` - Square footage of living space in the home
- `sqft_lot` - Square footage of the lot
- `floors` - Number of floors (levels) in house
- `waterfront` - Whether the house is on a waterfront
- `view` - Quality of view from house
- `condition` - How good the overall condition of the house is. Related to maintenance of house.
- `grade` - Overall grade of the house. Related to the construction and design of the house.
- `sqft_above` - Square footage of house apart from basement
- `sqft_basement` - Square footage of the basement
- `yr_built` - Year when house was built
- `yr_renovated` - Year when house was renovated
- `zipcode` - ZIP Code used by the United States Postal Service
- `lat` - Latitude coordinate
- `long` - Longitude coordinate
- `sqft_living15` - The square footage of interior housing living space for the nearest 15 neighbors
- `sqft_lot15` - The square footage of the land lots of the nearest 15 neighbors

In [4]:
```
#Importing needed libraries and visualizing the original dataframe as df
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from statsmodels.formula.api import ols
import statsmodels.api as sm
import matplotlib.pyplot as plt
from scipy import stats
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
df = pd.read_csv("D:\Moringa_windows_fld\Phase_2_Project\dsc-phase-2-project-v
# df = pd.read_csv("D:\Moringa_windows_fld\Phase_2_Project\dsc-phase-2-project
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   id             21597 non-null  int64  
 1   date           21597 non-null  object 
 2   price          21597 non-null  float64
 3   bedrooms       21597 non-null  int64  
 4   bathrooms      21597 non-null  float64
 5   sqft_living    21597 non-null  int64  
 6   sqft_lot       21597 non-null  int64  
 7   floors         21597 non-null  float64
 8   waterfront     19221 non-null  object 
 9   view           21534 non-null  object 
 10  condition      21597 non-null  object 
 11  grade          21597 non-null  object 
 12  sqft_above     21597 non-null  int64  
 13  sqft_basement  21597 non-null  object 
 14  yr_built       21597 non-null  int64  
 15  yr_renovated   17755 non-null  float64
 16  zipcode        21597 non-null  int64  
 17  lat            21597 non-null  float64
 18  long           21597 non-null  float64
 19  sqft_living15  21597 non-null  int64  
 20  sqft_lot15     21597 non-null  int64  
dtypes: float64(6), int64(9), object(6)
memory usage: 3.5+ MB
```

DATA PREPARATION

1. Cleaning the Data

In [5]:
```
# dropping columns not needed for the modelling process

filt_data = df.drop(columns=['date','view','sqft_above','sqft_basement','yr_re
filt_data
```

Out[5]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	con
0	7129300520	221900.0	3	1.00	1180	5650	1.0	NaN	A\
1	6414100192	538000.0	3	2.25	2570	7242	2.0	NO	A\
2	5631500400	180000.0	2	1.00	770	10000	1.0	NO	A\
3	2487200875	604000.0	4	3.00	1960	5000	1.0	NO	
4	1954400510	510000.0	3	2.00	1680	8080	1.0	NO	A\
...	...	...	...	...	...	...	...	...	
21592	263000018	360000.0	3	2.50	1530	1131	3.0	NO	A\
21593	6600060120	400000.0	4	2.50	2310	5813	2.0	NO	A\
21594	1523300141	402101.0	2	0.75	1020	1350	2.0	NO	A\
21595	291310100	400000.0	3	2.50	1600	2388	2.0	NaN	A\
21596	1523300157	325000.0	2	0.75	1020	1076	2.0	NO	A\

21597 rows × 11 columns

In [6]:
```
# Checking our filtered data for null values
filt_data.isna().sum()
```

Out[6]:
```
id               0
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront    2376
condition        0
grade            0
yr_built         0
dtype: int64
```

In [7]:
```
'''
We have 2376 missing values in the waterfront column
'''
```

Out[7]:
```
' \nWe have 2376 missing values in the waterfront column\n'
```

In [8]:
```
# Dealing with the missing values

filt_data['waterfront'].fillna('Missing Value',inplace=True)

# Checking if the waterfront still has missing values
filt_data.isna().sum()
```

Out[8]:
```
id             0
price          0
bedrooms       0
bathrooms      0
sqft_living    0
sqft_lot       0
floors         0
waterfront     0
condition      0
grade          0
yr_built       0
dtype: int64
```

In [9]:
```
filt_data.head()
```

Out[9]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	conditio
0	7129300520	221900.0	3	1.00	1180	5650	1.0	Missing Value	Averag
1	6414100192	538000.0	3	2.25	2570	7242	2.0	NO	Averag
2	5631500400	180000.0	2	1.00	770	10000	1.0	NO	Averag
3	2487200875	604000.0	4	3.00	1960	5000	1.0	NO	Ver Goo
4	1954400510	510000.0	3	2.00	1680	8080	1.0	NO	Averag

2. One Hot Encoding To Handle Numerical Columns

In [10]:
```
'''
The linear regression model cannot be built with categorical columns.
'''
```

Out[10]:
```
' \nThe linear regression model cannot be built with categorical columns.\n'
```

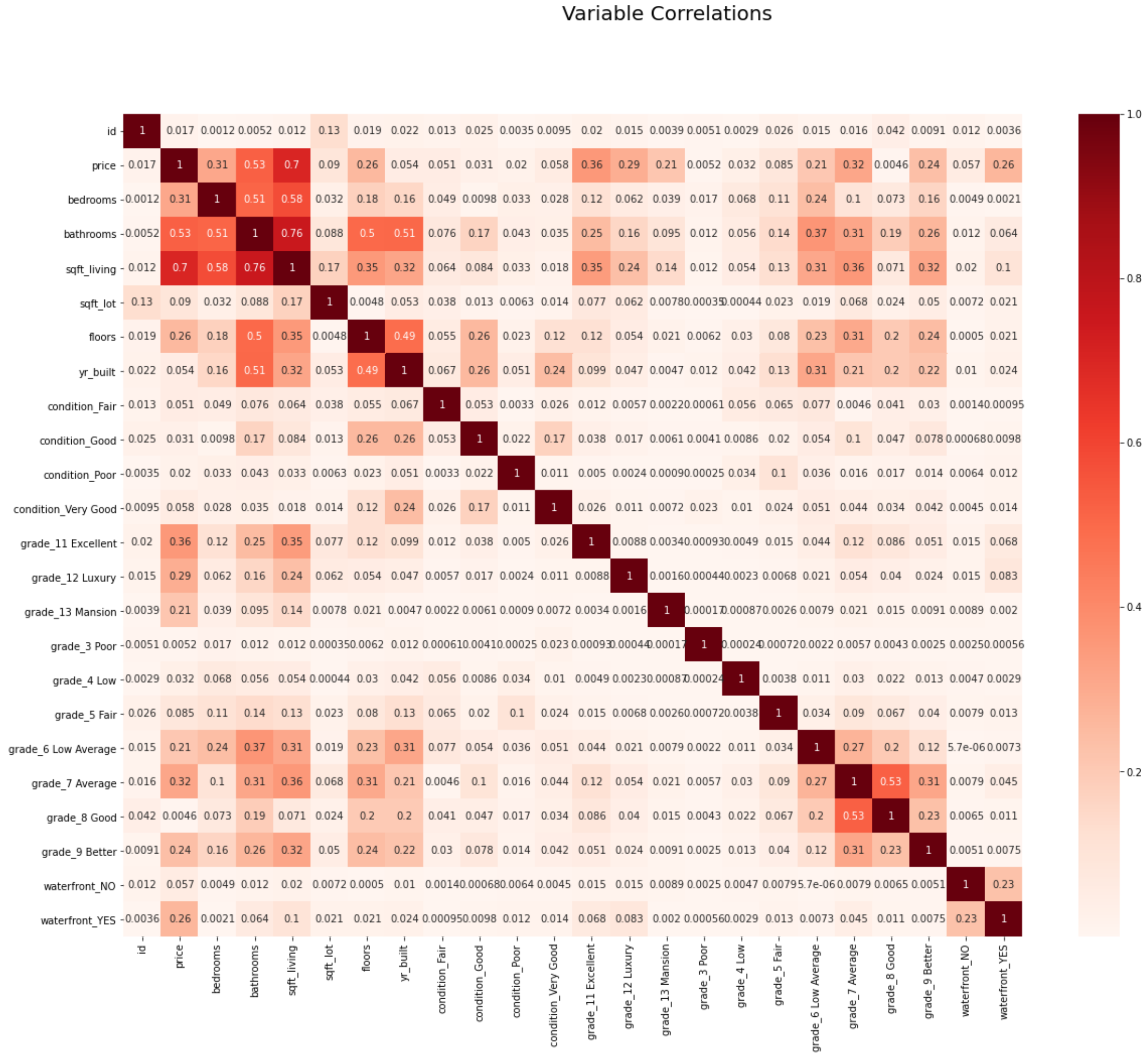
In [11]:
```
# Using one hot encoding for waterfront and condition which are categorical co
filt_data = pd.get_dummies(filt_data,columns=["condition","grade","waterfront"
filt_data
```

Out[11]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	yr_built	condit
0	7129300520	221900.0	3	1.00	1180	5650	1.0	1955	
1	6414100192	538000.0	3	2.25	2570	7242	2.0	1951	
2	5631500400	180000.0	2	1.00	770	10000	1.0	1933	
3	2487200875	604000.0	4	3.00	1960	5000	1.0	1965	
4	1954400510	510000.0	3	2.00	1680	8080	1.0	1987	
...	...	...	...	...	...	...	...	...	
21592	263000018	360000.0	3	2.50	1530	1131	3.0	2009	
21593	6600060120	400000.0	4	2.50	2310	5813	2.0	2014	
21594	1523300141	402101.0	2	0.75	1020	1350	2.0	2009	
21595	291310100	400000.0	3	2.50	1600	2388	2.0	2004	
21596	1523300157	325000.0	2	0.75	1020	1076	2.0	2008	

21597 rows × 24 columns

In [12]:
```
#Visualzing the correlation of different columns using a heat map

corr = filt_data.corr().abs()
fig, ax=plt.subplots(figsize=(20,15))
fig.suptitle('Variable Correlations', fontsize=20, y=.98, fontname='DejaVu San
heatmap = sns.heatmap(corr, cmap='Reds', annot=True)
```



Note that from above `sqft_living` has the highest correlation to the price column this will be used to create a simple linear regression model to show the change in `price` as to the change in `sqft_living`

MODELLING and REGRESSION RESULTS

SIMPLE LINEAR REGRESSION MODEL

In [13]:
```
'''
These are simple models for the most correlated columns with price which are s
us understand the relationship between the target variable and the independent
'''
```

Out[13]:
```
' \nThese are simple models for the most correlated columns with price which
are sqft_living, bathrooms, bedrooms and floors to help\nus understand the re
lationship between the target variable and the independent variables\n'
```

In [14]:
```
#Simple model for sqft_living
#formula y~x
sqft_living_formula = 'price ~ sqft_living '
sqft_living_model = ols(sqft_living_formula,filt_data).fit()

# Finding the predicted values and the residuals for plotting
predicted_values_sqft_living = sqft_living_model.fittedvalues
residuals_sqft_living = sqft_living_model.resid

sqft_living_model.summary()
```

Out[14]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.493
Model:	OLS	**Adj. R-squared:**	0.493
Method:	Least Squares	**F-statistic:**	2.097e+04
Date:	Sat, 04 Nov 2023	**Prob (F-statistic):**	0.00
Time:	12:56:45	**Log-Likelihood:**	-3.0006e+05
No. Observations:	21597	**AIC:**	6.001e+05
Df Residuals:	21595	**BIC:**	6.001e+05
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-4.399e+04	4410.023	-9.975	0.000	-5.26e+04	-3.53e+04
sqft_living	280.8630	1.939	144.819	0.000	277.062	284.664

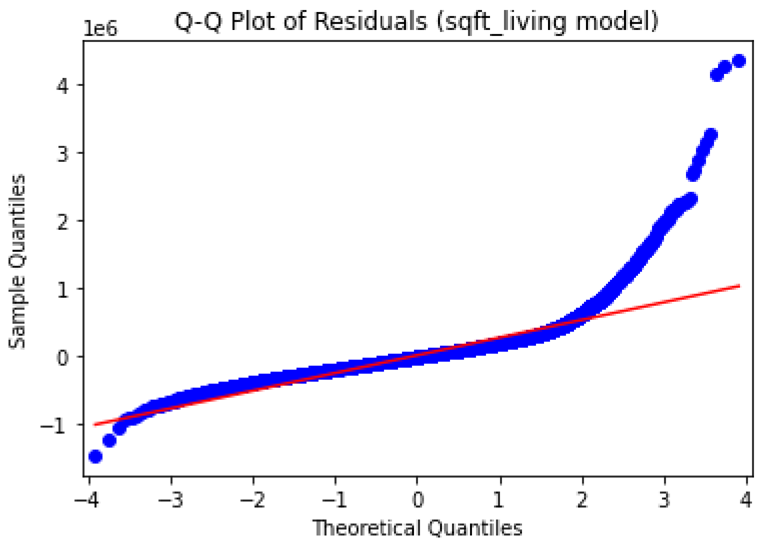
Omnibus:	14801.942	**Durbin-Watson:**	1.982
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	542662.604
Skew:	2.820	**Prob(JB):**	0.00
Kurtosis:	26.901	**Cond. No.**	5.63e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.63e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

In [15]:
```
'''
According to the above results, our model explains 49.3% of the variance in pr
Our model is statistically significant because our F-statistic p-value is less
The model coefficients(const and sqft_living are both statistically significan
For 1 square foot increase in living room, the price increases by 280.
If the sqft_living is 0, our price would be -4.399e+04(-43,990)
'''
```

Out[15]:
```
' \nAccording to the above results, our model explains 49.3% of the variance
in price.\nOur model is statistically significant because our F-statistic p-v
alue is less than 0.05\nThe model coefficients(const and sqft_living are both
statistically significant with t-statistic p-values less than 0.05\nFor 1 squ
are foot increase in living room, the price increases by 280.\nIf the sqft_li
ving is 0, our price would be -4.399e+04(-43,990)\n'
```

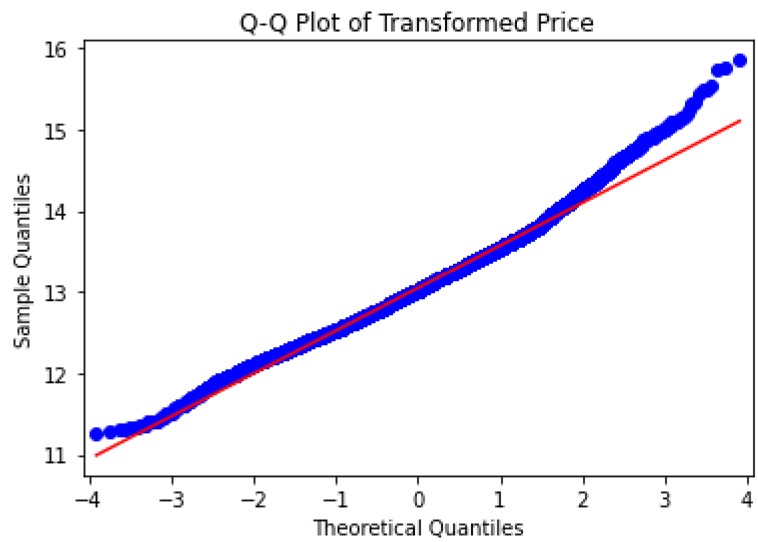
In [16]:
```
# Assuming 'sqft_living_model' is the fitted regression model

residuals_sqft_living = sqft_living_model.resid

# Create a Q-Q plot of the residuals
sm.qqplot(residuals_sqft_living, line='s')
plt.title('Q-Q Plot of Residuals (sqft_living model)')
plt.show()
```

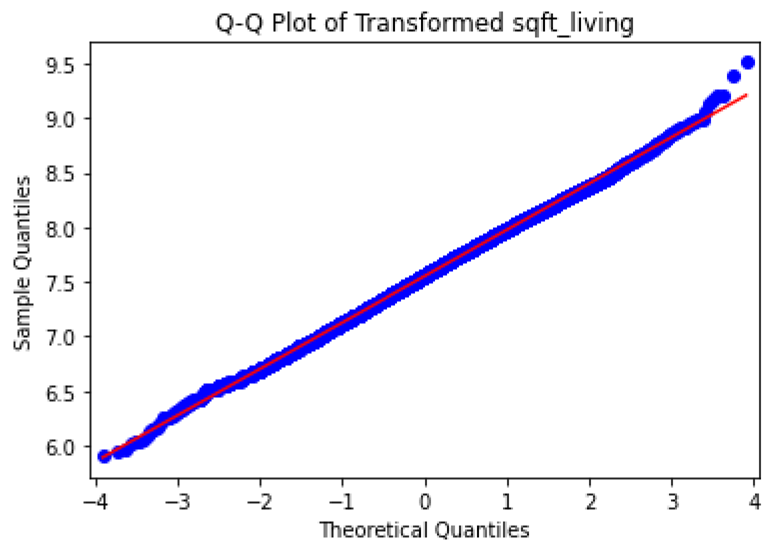


As we can see, this model violates the homoscedasticity and normality assumptions for linear regression. Log-transformation can often help when these assumptions are not met. Let's update the values to their natural logs and re-check the assumptions.

In [17]:
```
filt_data['price'] = np.log(filt_data['price'])
filt_data['sqft_living'] = np.log(filt_data['sqft_living'])
```

In [18]:
```
# Create a Q-Q plot for the 'price' variable
sm.qqplot(filt_data['price'], line='s')
plt.title('Q-Q Plot of Transformed Price')
plt.show()

# Create a Q-Q plot for the 'sqft_living' variable
sm.qqplot(filt_data['sqft_living'], line='s')
plt.title('Q-Q Plot of Transformed sqft_living')
plt.show()
```





In [19]:
```
'''
Now we've solved the heteroscedasticity problem for the most correlated column
'''
```

Out[19]:
```
" \nNow we've solved the heteroscedasticity problem for the most correlated c
olumn with price which is sqft_living\n"
```

In [20]:
```
#Simple linear regression model for bedrooms

bedrooms_formula = 'price ~ bedrooms'
bedrooms_model = ols(bedrooms_formula,filt_data).fit()

# Fitted values and residuals
predicted_values_bedrooms = bedrooms_model.fittedvalues
residuals_bedrooms= bedrooms_model.resid
bedrooms_model.summary()
```

Out[20]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.118
Model:	OLS	**Adj. R-squared:**	0.118
Method:	Least Squares	**F-statistic:**	2886.
Date:	Sat, 04 Nov 2023	**Prob (F-statistic):**	0.00
Time:	12:56:50	**Log-Likelihood:**	-15437.
No. Observations:	21597	**AIC:**	3.088e+04
Df Residuals:	21595	**BIC:**	3.089e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	12.3898	0.013	974.903	0.000	12.365	12.415
bedrooms	0.1952	0.004	53.724	0.000	0.188	0.202

Omnibus:	791.447	**Durbin-Watson:**	1.949
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1471.526
Skew:	0.290	**Prob(JB):**	0.00
Kurtosis:	4.140	**Cond. No.**	14.2

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [21]:
```
'''
Our bedrooms model explain 11.8% of our variance in prices
It is statistically significant because our f-statistic p-value is less than 0
'''
```

Out[21]:
```
' \nOur bedrooms model explain 11.8% of our variance in prices\nIt is statist
ically significant because our f-statistic p-value is less than 0.05\n'
```

In [22]:
```
# Simple linear regression Model for bathrooms

bathrooms_formula = 'price ~ bathrooms'
bathrooms_model = ols(bathrooms_formula,filt_data).fit()

# Fitted values and residuals
predicted_values_bathrooms = bathrooms_model.fittedvalues
residuals_bathrooms = bathrooms_model.resid
bathrooms_model.summary()
```

Out[22]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.304
Model:	OLS	**Adj. R-squared:**	0.304
Method:	Least Squares	**F-statistic:**	9427.
Date:	Sat, 04 Nov 2023	**Prob (F-statistic):**	0.00
Time:	12:56:50	**Log-Likelihood:**	-12880.
No. Observations:	21597	**AIC:**	2.576e+04
Df Residuals:	21595	**BIC:**	2.578e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	12.2496	0.009	1399.614	0.000	12.232	12.267
bathrooms	0.3775	0.004	97.092	0.000	0.370	0.385

Omnibus:	191.594	**Durbin-Watson:**	1.958
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	196.538
Skew:	0.232	**Prob(JB):**	2.10e-43
Kurtosis:	3.063	**Cond. No.**	7.76

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [23]:
```
#Simple Linear regression Model for floors

floors_formula = 'price ~ floors'
floors_model = ols(floors_formula,filt_data).fit()

# Fitted values and residuals
predicted_values_floors = floors_model.fittedvalues
residuals_floors = floors_model.resid
floors_model.summary()
```

Out[23]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.096
Model:	OLS	**Adj. R-squared:**	0.096
Method:	Least Squares	**F-statistic:**	2306.
Date:	Sat, 04 Nov 2023	**Prob (F-statistic):**	0.00
Time:	12:56:50	**Log-Likelihood:**	-15696.
No. Observations:	21597	**AIC:**	3.140e+04
Df Residuals:	21595	**BIC:**	3.141e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	12.5954	0.010	1256.346	0.000	12.576	12.615
floors	0.3031	0.006	48.023	0.000	0.291	0.315

Omnibus:	836.437	**Durbin-Watson:**	1.971
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1031.279
Skew:	0.437	**Prob(JB):**	1.15e-224
Kurtosis:	3.618	**Cond. No.**	6.37

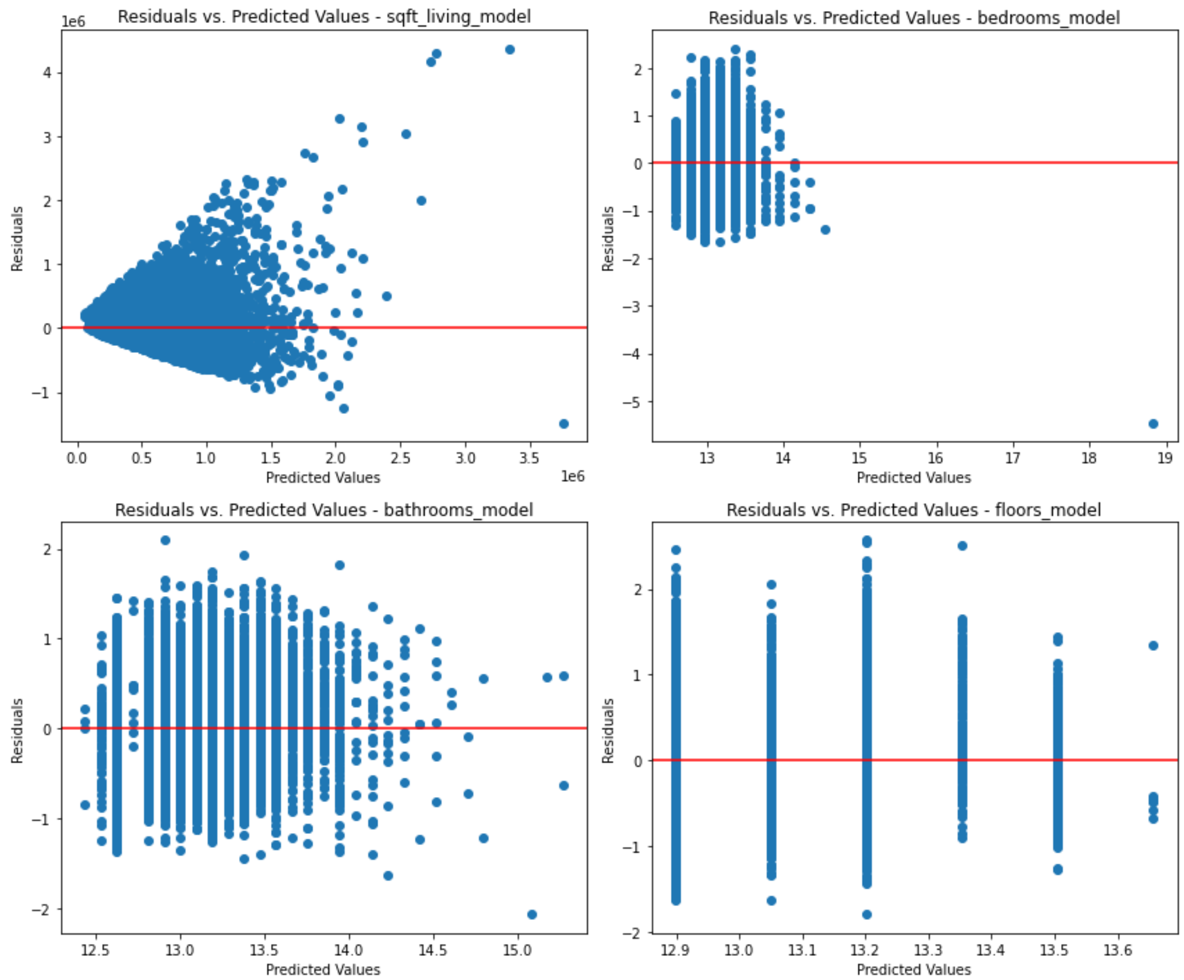
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [24]:
```
'''
Our rooms model explain 9.6% of our variance in prices
It is statistically significant because our f-statistic p-value is less than 0
'''
```

Out[24]:
```
' \nOur rooms model explain 9.6% of our variance in prices\nIt is statistical
ly significant because our f-statistic p-value is less than 0.05\n'
```

The scatter plots below are to show if the data has the character of heteroscedasticity, which will be observed if the spread of the residuals changes systematically as predicted values change by forming a defined shape like a cone or a funnel-like pattern.

In [25]:
```
fig, axs = plt.subplots(2, 2, figsize=(12, 10))

# List of predicted_values and residuals for each model

predicted_values_list = [predicted_values_sqft_living, predicted_values_bedroo
residuals_list = [residuals_sqft_living, residuals_bedrooms, residuals_bathroo
model_names = ['sqft_living_model', 'bedrooms_model', 'bathrooms_model', 'floo

for i, ax in enumerate(axs.flatten()):
    ax.scatter(predicted_values_list[i], residuals_list[i])
    ax.axhline(y=0, color='r', linestyle='-')
    ax.set_title(f"Residuals vs. Predicted Values - {model_names[i]}")
    ax.set_xlabel('Predicted Values')
    ax.set_ylabel('Residuals')

plt.tight_layout()
plt.show()
```



In [26]:
```
'''
From the plots above, our residuals are normally distributed because there is
of points away from the origin .
The residuals are symmetric around the origin
'''
```

Out[26]:
```
' \nFrom the plots above, our residuals are normally distributed because ther
e is a high density of points close to the origin and a low density\nof point
s away from the origin .\nThe residuals are symmetric around the origin\n'
```

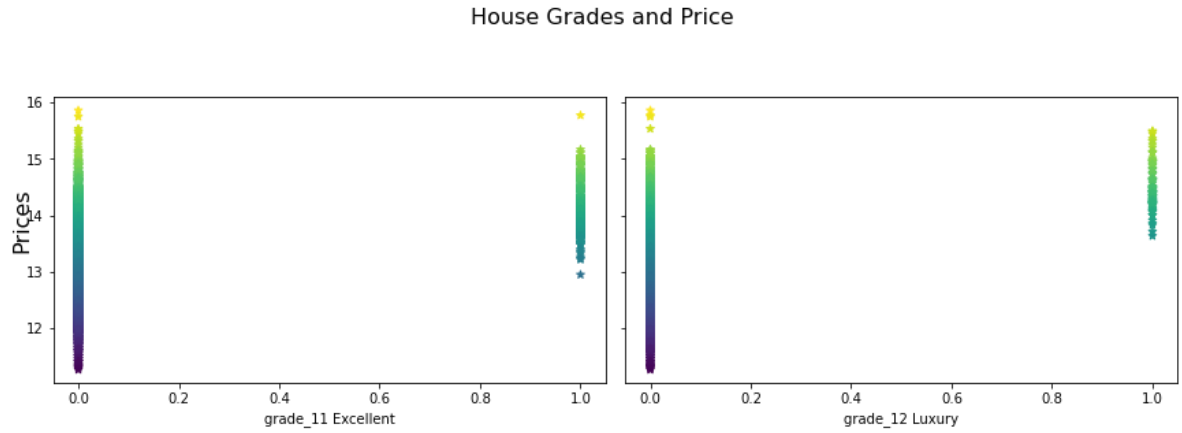
In [27]:
```
# Slope (coefficient of x, y=0)

m = sqft_living_model.params['sqft_living']
# Intercept (coefficient of Intercept)
b = sqft_living_model.params['Intercept']


print(f"""
Our simple linear regression model found a y-intercept
of ${round(b, 2)}, then for every increase of 1 square foot
above-living area, the price increases by ${round(m, 2)}
""")
```

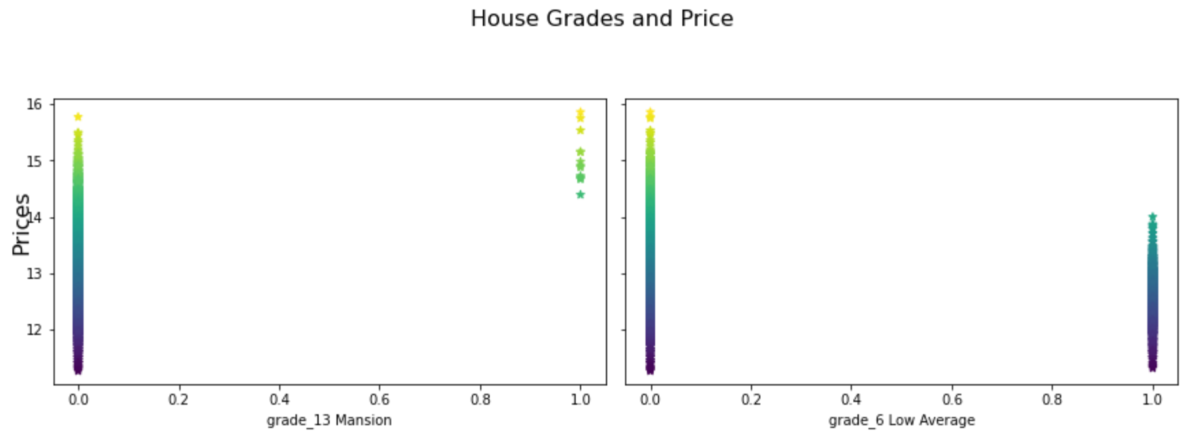
```
Our simple linear regression model found a y-intercept
of $-43988.89, then for every increase of 1 square foot
above-living area, the price increases by $280.86
```

MULTIPLE LINEAR REGRESSION MODEL

Before building the multiple linear regression model, We completed a simple linear regession analysis for(`sqft_living` , `bedrooms` , `bathrooms` and `floors`), they had the highest correlation to `price` with no violation to multicollinearity assumption. Also they do not present heteroscedasticity hence they do not violate the assumption of homoscedasticity.

In [28]:
```
# Using a function to show linear relationship of price and one-hot encoded co

def plot_scatter(columns, price):
    num_columns = len(columns)

    # Creating a figure for plotting
    fig, axes = plt.subplots(1, num_columns, sharex=False, sharey=True, figsiz

    # Setting title and labels
    fig.suptitle('House Grades and Price', fontsize=16, y=1.1, fontname='DejaV
    fig.text(0.0001, 0.56, 'Prices', va='center', rotation='vertical', fontsiz

    for i, column in enumerate(columns):
        if num_columns == 2:
            # Scatter plot for two columns
            sc = axes[i].scatter(column, price, c=price, marker="*")
            axes[i].set_xlabel(column.name)

    # Adjusting the layout and displaying the plot
    fig.tight_layout()
    plt.show()

# Example usage:
columns_to_plot = [
    [filt_data['grade_11 Excellent'], filt_data['grade_12 Luxury']],
    [filt_data['grade_13 Mansion'], filt_data['grade_6 Low Average']],
    [filt_data['grade_7 Average']]
]

for column_pair in columns_to_plot:
    # Filter out pairs with only one column
    if len(column_pair) > 1:
        plot_scatter(column_pair, filt_data['price'])
```





From the above plots, grade_6 Low Average and grade_12 Luxury have the most pronounced relationship hence they will be used in the model.

Model 1

In [29]:
```
#Model 1(With numerical columns only)
multiple_formula_1 = 'price ~ sqft_living + bathrooms + bedrooms + floors'
# Fit the model
multiple_model_1 = ols(multiple_formula_1, filt_data).fit()
print(multiple_model_1.summary())
```

```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:                  price   R-squared:                       0.47
1
Model:                            OLS   Adj. R-squared:                  0.47
0
Method:                 Least Squares   F-statistic:                     479
8.
Date:                Sat, 04 Nov 2023   Prob (F-statistic):               0.0
0
Time:                        12:57:01   Log-Likelihood:                -9924.
1
No. Observations:               21597   AIC:                         1.986e+0
4
Df Residuals:                   21592   BIC:                         1.990e+0
4
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
==
                  coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
--
Intercept       6.7566      0.067    100.441      0.000       6.625       6.8
88
sqft_living     0.8417      0.010     80.702      0.000       0.821       0.8
62
bathrooms       0.0522      0.006      9.203      0.000       0.041       0.0
63
bedrooms       -0.0714      0.004    -19.689      0.000      -0.079      -0.0
64
floors          0.0443      0.006      7.881      0.000       0.033       0.0
55
==============================================================================
=
Omnibus:                      123.973   Durbin-Watson:                   1.98
0
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              124.40
9
Skew:                           0.177   Prob(JB):                    9.66e-2
8
Kurtosis:                       2.888   Cond. No.                        22
9.
==============================================================================
=

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
```

''' Our model has an r-squared value of 47.1 and therefore explains 47.1% of the variance in price It is also statistically significant because our f-statistic p-value is less than 0.05 All coefficients are also statistically significant as they have a t-statistica p-value of less than 0.05

i)sqft_living(0.8417) A one unit increase in square footage of the living room is associated with an estimated increase of 0.8417 units in price, assuming all other variables are held constant. Suggesting that larger living areas are positively correlated with higher house prices.

ii)bathrooms(0.0522) A one unit increase in the number of bathrooms leads to a 0.0522 increase in price units.Hence the higher the number of bathrooms the higher the price.

iii)bedrooms(-0.0714) A unit increase in the number of bedrooms leads to a decrease of 0.0714 units in price. Meaning bedrooms is negatively correlated with price. '''

Model 2

In [31]:
```
filt_data.columns
```

Out[31]:
```
Index(['id', 'price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot',
       'floors', 'yr_built', 'condition_Fair', 'condition_Good',
       'condition_Poor', 'condition_Very Good', 'grade_11 Excellent',
       'grade_12 Luxury', 'grade_13 Mansion', 'grade_3 Poor', 'grade_4 Low',
       'grade_5 Fair', 'grade_6 Low Average', 'grade_7 Average',
       'grade_8 Good', 'grade_9 Better', 'waterfront_NO', 'waterfront_YES'],
      dtype='object')
```

In [32]:
```
# Using numerical columns and the most correlated categorical columns with pri

filt_data.rename(columns={'grade_7 Average': 'Average_7', 'grade_12 Luxury': '

multiple_formula_2 = 'price ~ sqft_living + bathrooms + bedrooms + floors + Av

# Fit the model
multiple_model_2 = ols(multiple_formula_2, filt_data).fit()
print(multiple_model_2.summary())
```

```
                            OLS Regression Results                            
==============================================================================
=
Dep. Variable:                  price   R-squared:                       0.48
6
Model:                            OLS   Adj. R-squared:                  0.48
6
Method:                 Least Squares   F-statistic:                     340
2.
Date:                Sat, 04 Nov 2023   Prob (F-statistic):               0.0
0
Time:                        12:57:01   Log-Likelihood:                -9605.
3
No. Observations:               21597   AIC:                         1.922e+0
4
Df Residuals:                   21590   BIC:                         1.928e+0
4
Df Model:                           6                                         
Covariance Type:            nonrobust                                         
==============================================================================
==
                  coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
--
Intercept       7.1978      0.069    104.759      0.000       7.063       7.3
32
sqft_living     0.7912      0.010     75.513      0.000       0.771       0.8
12
bathrooms       0.0406      0.006      7.233      0.000       0.030       0.0
52
bedrooms       -0.0593      0.004    -16.456      0.000      -0.066      -0.0
52
floors          0.0258      0.006      4.578      0.000       0.015       0.0
37
Average_7      -0.1211      0.006    -21.291      0.000      -0.132      -0.1
10
Luxury_12       0.5705      0.041     13.996      0.000       0.491       0.6
50
==============================================================================
=
Omnibus:                       99.478   Durbin-Watson:                   1.98
1
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               99.55
1
Skew:                           0.158   Prob(JB):                    2.41e-2
2
Kurtosis:                       2.896   Cond. No.                        23
8.
==============================================================================
=

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
```

''' Our r-squared value has increased to 48.6 meaning our model explains 48.6% of the variance in prices Our model is statistically significant because the f-statistic p-value is less than 0.05 The coefficients are also statistically significant because the t-statistic p-values are less than 0.05

i) sqft_living An increase in one unit of square foot in the living room leads to a 0.7912 increase in price units. Hence positively related.

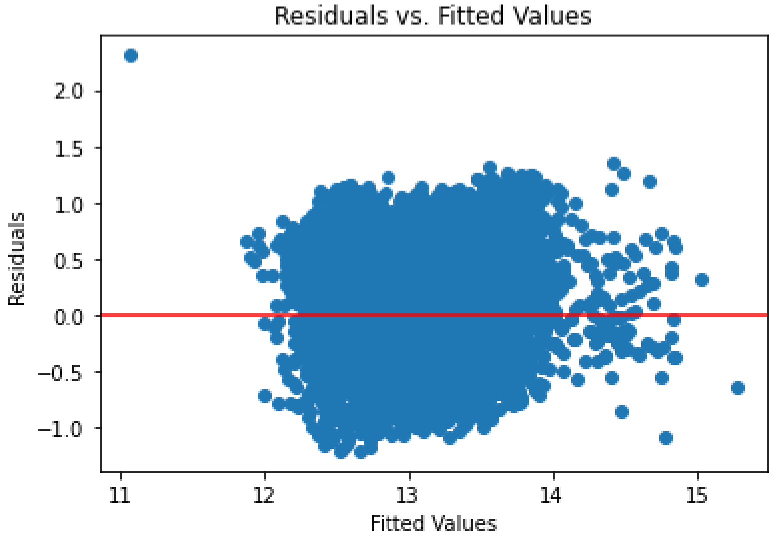
ii) bathrooms A one unit increase in the number of bathrooms leads to a 0.0406 increase in price units.Hence the higher the number of bathrooms the higher the price.

iii) bedrooms iii)bedrooms(-0.0714) A unit increase in the number of bedrooms leads to a decrease of 0.0593 units in price. Meaning bedrooms is negatively correlated with price.

iv) Average_7 A unit increase in the grade of grade_7 houses leades to a decrease of 0.1211 units in price. Thus as grade 7 houses increase there is a decrease in house prices

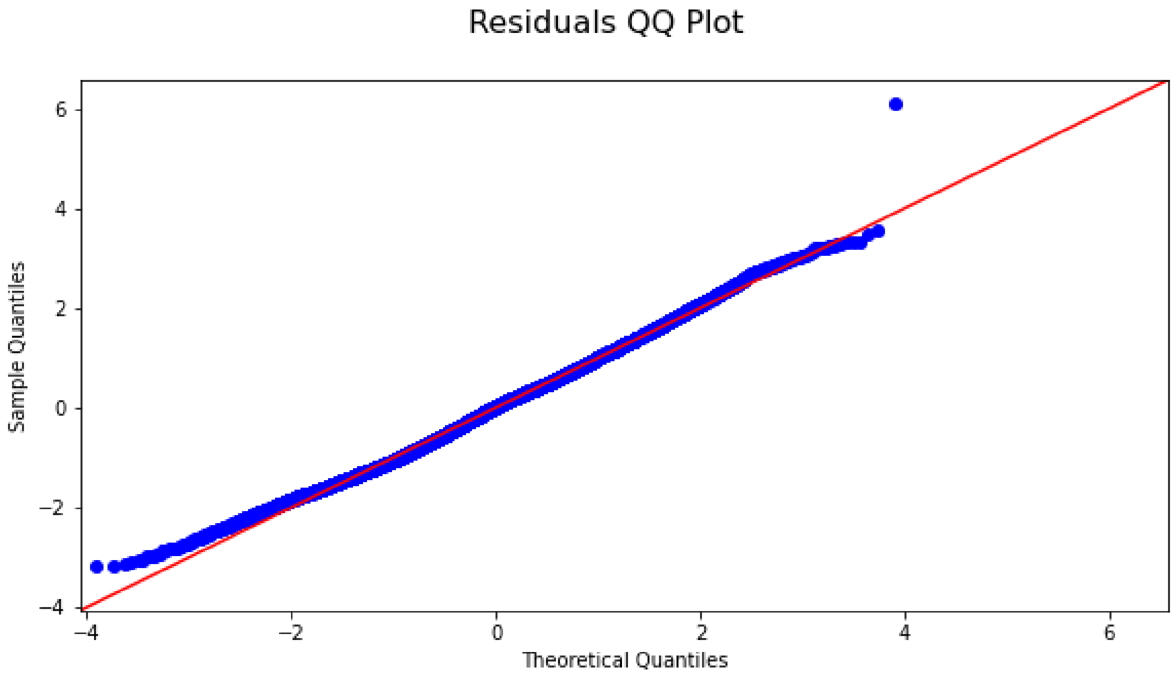
v) Luxury_12 A one unit increase in grade_12 houses causes a 0.5705 increase in prices. '''

In [34]:
```
# #Residuals vs. Fitted Values Plot to check for Homoscedasticity

# Assuming 'multiple_model_2' is the fitted regression model

residuals = multiple_model_2.resid
fitted_values = multiple_model_2.fittedvalues

# Plot residuals against fitted values to check for homoscedasticity
plt.scatter(fitted_values, residuals)
plt.axhline(y=0, color='r', linestyle='-')  # Adding a horizontal line at y=0
plt.title('Residuals vs. Fitted Values')
plt.xlabel('Fitted Values')
plt.ylabel('Residuals')
plt.show()
```



In [35]:
```
# Test for Normality of Residuals

# Assuming 'multiple_model_2' is the fitted regression model
residuals = multiple_model_2.resid
fitted_values = multiple_model_2.fittedvalues

# Plot residuals against fitted values to check for homoscedasticity
fig = sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True)
fig.suptitle('Residuals QQ Plot', fontsize=16, fontname='DejaVu Sans')
fig.set_size_inches(10, 5)
fig.show()
```

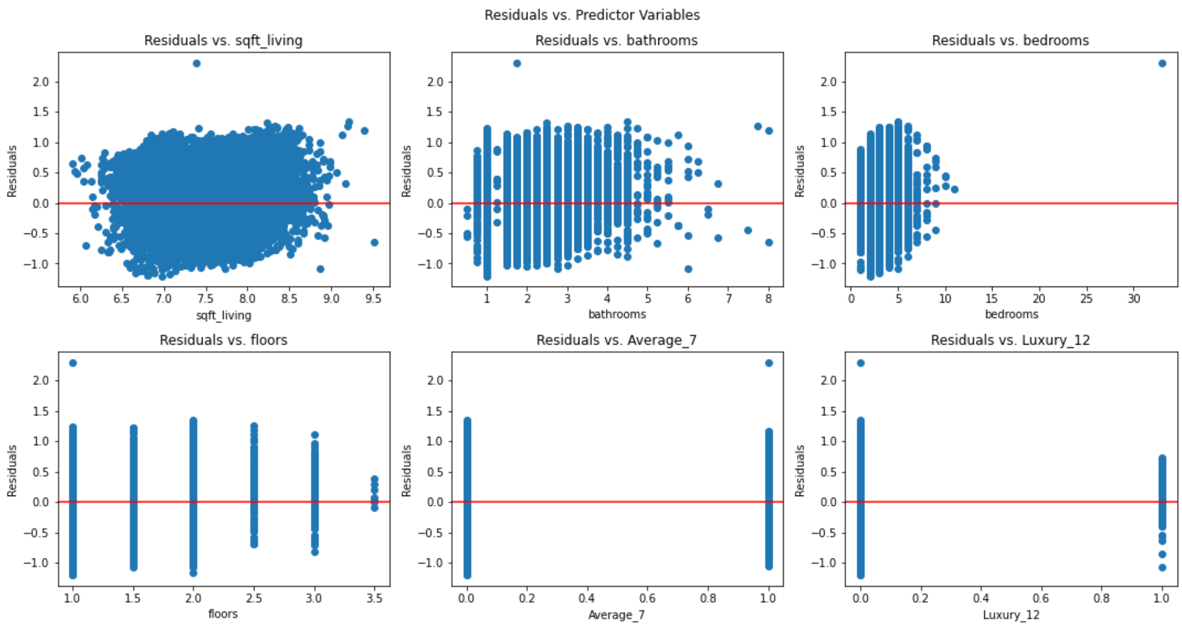
```
<ipython-input-35-9dd58271b716>:11: UserWarning: Matplotlib is currently usin
g module://ipykernel.pylab.backend_inline, which is a non-GUI backend, so can
not show the figure.
  fig.show()
```



In [36]:
```
'''
The residuals are normally distributed thus our model passes the assumption of
'''
```

Out[36]:
```
' \nThe residuals are normally distributed thus our model passes the assumpti
on of normality.\n'
```

In [37]:
```
# Residuals vs. Predictor Variables (for linearity and independence)
# Assuming 'X' contains predictor variables used in the model

X = filt_data[['sqft_living', 'bathrooms', 'bedrooms', 'floors', 'Average_7',

# Create a grid of subplots
fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(15, 8))
fig.suptitle("Residuals vs. Predictor Variables")

# Flatten the 2D array of subplots into a 1D array
axes = axes.flatten()

for i, col in enumerate(X):
    ax = axes[i]
    ax.scatter(X[col], multiple_model_2.resid)
    ax.axhline(y=0, color='r', linestyle='-')
    ax.set_xlabel(col)
    ax.set_ylabel('Residuals')
    ax.set_title(f'Residuals vs. {col}')

# Adjust spacing and display the plot
plt.tight_layout()
plt.show()
```



VALIDATION OF THE MODEL

The following code performs cross validation to assess the performance of our model and generalization of unseen data.

In [38]:
```
# X' contains the predictors and 'y' contains the target variable from your da
X = filt_data[['sqft_living', 'bathrooms', 'bedrooms', 'floors', 'Average_7',
y = filt_data['price']

# Split the data into training and test sets (75% training, 25% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, rand

# Create a linear regression model
multiple_model_2 = LinearRegression()

# Fit the model on the training data
multiple_model_2.fit(X_train, y_train)

# Perform cross-validation and calculate both R^2 and mean squared error
cv_scores_r2 = cross_val_score(multiple_model_2, X_train, y_train, cv=5, scori
cv_scores_mse = -cross_val_score(multiple_model_2, X_train, y_train, cv=5, sco

# Print the cross-validation scores
print("Cross-validation R^2 scores:", cv_scores_r2)
print("Mean R^2 score:", np.mean(cv_scores_r2))
print("Cross-validation MSE scores:", cv_scores_mse)
print("Mean MSE:", np.mean(cv_scores_mse))

# Evaluate the model on the test set
y_pred_test = multiple_model_2.predict(X_test)
test_r2 = multiple_model_2.score(X_test, y_test)
test_mse = mean_squared_error(y_test, y_pred_test)
print("Test R^2 score:", test_r2)
print("Test MSE:", test_mse)
```

```
Cross-validation R^2 scores: [0.48161229 0.48059014 0.50803613 0.48848282 0.4
6995118]
Mean R^2 score: 0.4857345142675077
Cross-validation MSE scores: [0.14732577 0.14226421 0.1402082  0.14219079 0.1
4271437]
Mean MSE: 0.14294066536015956
Test R^2 score: 0.4833251170315963
Test MSE: 0.1418661043082534
```

CONCLUSION

The best price predictor o.f house price during renovations with the intent to sell in King's county is sqft_living and grade.As home owner plan to renovate their house and add more square footage of space they must also make sure their building grade is as close to the best as possible to increase the value of one's house.

The model has its limitations as the need to log-transform one of the variables to satisfy the regression assumptions, any new data input needs to undergo the same preprocessing.Without the use of regional data it must be remebered that house value may differ according their zipcodes

Future analysis should explore better predictors of the prices of homes outside King County.