Toronto House Price Analysis Based on Amenities

In [1]:
```
# import packages/libraries
import pandas as pd
import matplotlib.pylab as plt
import seaborn as sns
```

In [152]:
```
# https://www.kaggle.com/datasets/rajacsp/toronto-apartment-price?resource=do
# load data
TorontoHousing_df = pd.read_csv("DataFiles\Toronto_apartment_rentals_2018.csv
TorontoHousing_df.head(12)
```

Out[152]:

	Bedroom	Bathroom	Den	Address	Lat	Long	Price
0	2	2.0	0	3985 Grand Park Drive, 3985 Grand Park Dr, Mis...	43.581639	-79.648193	$2,450.00
1	1	1.0	1	361 Front St W, Toronto, ON M5V 3R5, Canada	43.643051	-79.391643	$2,150.00
2	1	1.0	0	89 McGill Street, Toronto, ON, M5B 0B1	43.660605	-79.378635	$1,950.00
3	2	2.0	0	10 York Street, Toronto, ON, M5J 0E1	43.641087	-79.381405	$2,900.00
4	1	1.0	0	80 St Patrick St, Toronto, ON M5T 2X6, Canada	43.652487	-79.389622	$1,800.00
5	1	1.0	0	87 Jameson Avenue, Toronto, ON, M6K 2W8	43.634890	-79.434654	$1,729.00
6	2	1.0	0	700 Ross Street, Burlington, ON, L7S 1S2	43.328986	-79.808618	$1,685.00
7	1	1.0	0	25 Telegram Mews, Toronto, ON, M5V 3Z2	43.640918	-79.393982	$1,900.00
8	1	1.0	0	560 Front St W, toronto, ON, M5V 0L5	43.641308	-79.400093	$1,900.00
9	1	1.0	1	70 Queens Wharf Rd 33rd Floor, Toronto, ON M5V...	43.640068	-79.399960	$2,400.00
10	1	1.0	0	545 - 555 Sherbourne Street, Toronto, ON, M4X...	43.668468	-79.374834	$1,750.00
11	2	1.0	0	545 - 555 Sherbourne Street, Toronto, ON, M4X...	43.668468	-79.374834	$2,000.00

In [153]:
```
# Inspect data dimensions
TorontoHousing_df.shape
```

Out[153]: (1124, 7)

Data Cleaning

Duplicates

In [154]:
```python
# Check for duplicated rows.
duplicate_count = TorontoHousing_df.duplicated().sum()
print(duplicate_count)
```

```
308
```

In [155]:
```python
# Inspect / View duplicates
TorontoHousing_df[TorontoHousing_df.duplicated()].sort_values(by=['Bedroom',
```

Out[155]:

	Bedroom	Bathroom	Den	Address	Lat	Long	Price
254	1	1.0	0	# Dundas st w, Denison ave and Dundas st w M5T...	43.652043	-79.402242	$1,300.00
386	1	1.0	0	# Dundas st w, Denison ave and Dundas st w M5T...	43.652043	-79.402242	$1,300.00
232	1	1.0	0	, DOWNTOWN M5V 4A9 ON, Canada	43.640402	-79.397147	$2,100.00
365	1	1.0	0	, DOWNTOWN M5V 4A9 ON, Canada	43.640402	-79.397147	$2,100.00
460	1	1.0	0	, DOWNTOWN M5V 4A9 ON, Canada	43.640402	-79.397147	$2,100.00
...	...	...	...	...	...	...	...
418	3	1.5	0	19 Sudbury St, Toronto, ON M6J 3W6, Canada	43.641109	-79.419448	$3,450.00
214	3	1.5	0	2304 Weston Road, Toronto, ON, M9N 1Z3	43.705123	-79.530091	$2,050.00
345	3	1.5	0	2304 Weston Road, Toronto, ON, M9N 1Z3	43.705123	-79.530091	$2,050.00
402	3	2.0	0	, M5V 2G4, Toronto, ON	43.646764	-79.392221	$3,200.00
401	3	2.0	0	M5B0A5, Canada	56.130366	-106.346771	$4,000.00

308 rows × 7 columns

In [156]:
```python
# drop duplicate rows
df_cleaned = TorontoHousing_df.drop_duplicates().copy()
```

In [157]:
```python
# Confirm duplicate rows were dropped
duplicate_count = df_cleaned.duplicated().sum()
print(duplicate_count)
```

```
0
```

Missing Values

In [158]:
```
# Check for missing values.
missing_values = df_cleaned.isnull().sum()
print(missing_values)
```

```
Bedroom      0
Bathroom     0
Den          0
Address      0
Lat          0
Long         0
Price        0
dtype: int64
```

Data Types

In [159]:
```
# Check columns data types
df_cleaned.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 816 entries, 0 to 1123
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Bedroom   816 non-null    int64  
 1   Bathroom  816 non-null    float64
 2   Den       816 non-null    int64  
 3   Address   816 non-null    object 
 4   Lat       816 non-null    float64
 5   Long      816 non-null    float64
 6   Price     816 non-null    object 
dtypes: float64(3), int64(2), object(2)
memory usage: 51.0+ KB
```

In [160]:
```
df_cleaned.Price.head(12)
```

Out[160]:
```
0     $2,450.00
1     $2,150.00
2     $1,950.00
3     $2,900.00
4     $1,800.00
5     $1,729.00
6     $1,685.00
7     $1,900.00
8     $1,900.00
9     $2,400.00
10    $1,750.00
11    $2,000.00
Name: Price, dtype: object
```

Remove the characters '$' and ',' from the `Price` variable.
Then convert the variable into a `float` data type

In [161]:

```python
# Remove non-numeric values, and convert to float
df_cleaned.Price = df_cleaned.Price.str.replace('$','', regex=True)
df_cleaned.Price = df_cleaned.Price.str.replace(',','', regex=True)
df_cleaned.Price = df_cleaned.Price.astype(float)
```

In [162]:

```python
# Confirm data type changes
df_cleaned.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 816 entries, 0 to 1123
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Bedroom   816 non-null    int64
 1   Bathroom  816 non-null    float64
 2   Den       816 non-null    int64
 3   Address   816 non-null    object
 4   Lat       816 non-null    float64
 5   Long      816 non-null    float64
 6   Price     816 non-null    float64
dtypes: float64(4), int64(2), object(1)
memory usage: 51.0+ KB
```

In [163]:

```python
# Summary statistics
df_cleaned.describe()
```

Out[163]:

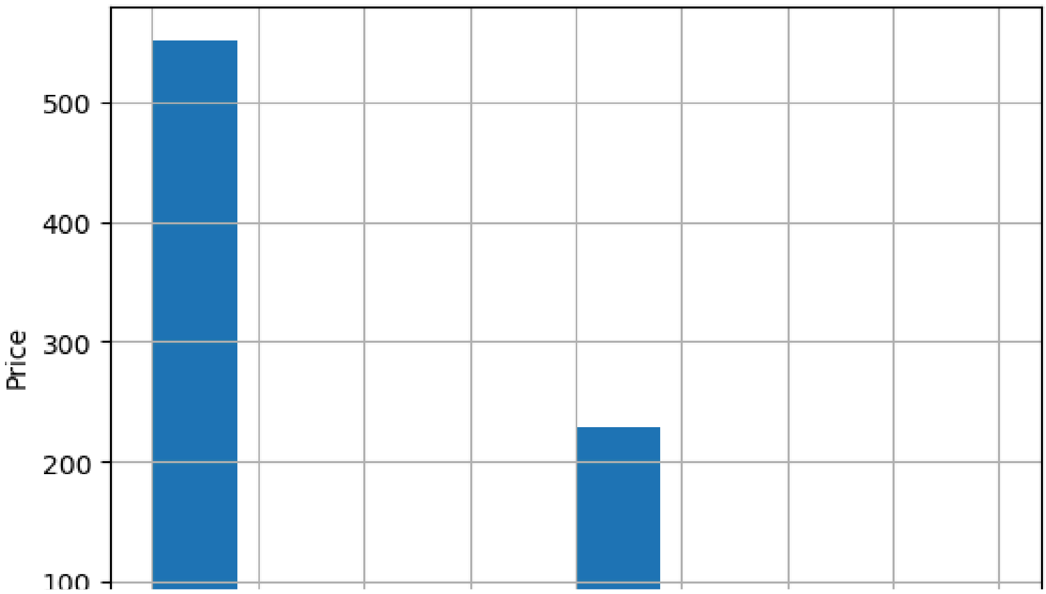
	Bedroom	Bathroom	Den	Lat	Long	Price
count	816.000000	816.000000	816.000000	816.000000	816.000000	816.000000
mean	1.367647	1.239583	0.154412	43.707321	-79.497995	2873.492647
std	0.566667	0.438082	0.361565	0.683253	1.836522	18707.483551
min	1.000000	1.000000	0.000000	42.985767	-114.082215	65.000000
25%	1.000000	1.000000	0.000000	43.641617	-79.412034	1750.000000
50%	1.000000	1.000000	0.000000	43.652023	-79.387374	2100.000000
75%	2.000000	1.000000	0.000000	43.667670	-79.376923	2500.000000
max	3.000000	3.000000	1.000000	56.130366	-73.576385	535000.000000

In [164]:
```python
# Histogram - Price
df_cleaned['Price'].plot.hist()
```

Out[164]: <AxesSubplot:ylabel='Frequency'>

In [165]:
```python
# Historgram Price-BedRoom
Housing_Hist = df_cleaned.Bedroom.hist()
Housing_Hist.set_xlabel('Bedroom');
Housing_Hist.set_ylabel('Price')
```

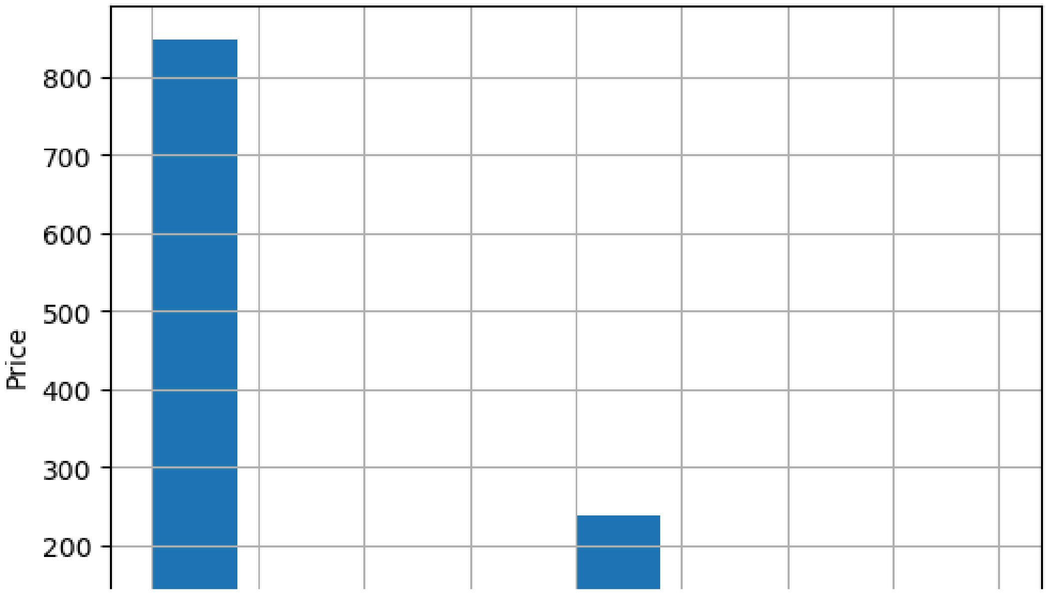
Out[165]: Text(0, 0.5, 'Price')



In [166]:
```
# Historgram Price-BathRoom

Housing_Hist = TorontoHousing_df.Bathroom.hist()
Housing_Hist.set_xlabel('Bathroom');
Housing_Hist.set_ylabel('Price')
```

Out[166]: `Text(0, 0.5, 'Price')`



Detect Outliers

In [167]:
```
sns.boxplot(y=df_cleaned.Price, x=df_cleaned.Bedroom, showmeans=True)
```

Out[167]: `<AxesSubplot:xlabel='Bedroom', ylabel='Price'>`

The boxplot is showing a similar behaviour, as with the histogram. We can see a value point that is extremely distant from the the rest of the data points. Again this can be due to outlier values

Calculate lower and upper interquartile range

We will use these values to evaluate and remove outliers.

In [168]:
```python
# Set q1 and q3
q1 = df_cleaned.Price.quantile(0.25)
q3 = df_cleaned.Price.quantile(0.75)

# Calculate IQR
iqr = q3 - q1

# Calculate lower and upper bounds
lower_bound = q1 - (1.5 * iqr)
upper_bound = q3 + (1.5 * iqr)

print("lower: {}, upper: {}".format(lower_bound, upper_bound))
```

```
lower: 625.0, upper: 3625.0
```

In [169]:
```python
# Inspect outliers
df_outliers = df_cleaned.query("Price < @lower_bound | Price > @upper_bound")
df_outliers.head(12)
```

Out[169]:

	Bedroom	Bathroom	Den	Address	Lat	Long	Price
816	1	2.0	0	Euclid Ave, Toronto, ON, Canada	43.658689	-79.412577	65.0
973	1	2.0	1	2121 Lake Shore Blvd W, Etobicoke, ON M8V 4E9,...	43.627447	-79.478374	99.0
794	1	1.0	0	8 Wellesley St E, Toronto, ON M4Y 3B2, Canada	43.665233	-79.384293	99.0
761	1	1.0	0	, Toronro M4V 1N5 ON, Canada	43.686511	-79.399522	150.0
1110	1	1.0	0	195 Wynford Dr, North York, ON M3C 3P3, Canada	43.723587	-79.324879	300.0
83	1	1.0	0	89 Chestnut St, Toronto, ON M5G 1R1, Canada	43.654155	-79.385211	550.0
1049	2	1.0	0	Bathurst St, Toronto, ON M5S 2P9, Canada	43.658278	-79.408437	600.0
1057	2	1.0	0	, Toronto M5T 0A9 ON, Canada	43.652519	-79.389078	3700.0
91	2	2.0	0	28 Wellesley St E, Toronto, ON M4Y, Canada	43.665588	-79.383028	3700.0
644	1	1.0	0	49 McCaul St, Toronto, ON M5T 1V7, Canada	43.651579	-79.390080	3750.0
884	1	1.0	0	101 Peter St, Toronto, ON M5V 0G6, Canada	43.647513	-79.392702	3750.0
695	3	2.0	0	14 York St, Toronto, ON M5J 0B1, Canada	43.641908	-79.381780	3800.0

In [170]:
```python
# Inspect outliers
df_outliers.tail(12)
```

Out[170]:

	Bedroom	Bathroom	Den	Address	Lat	Long	Price
1031	2	2.0	0	30 Nelson St, Toronto, ON M5V 0H5, Canada	43.649023	-79.388400	4500.0
902	3	3.0	0	10 Glen Rd, Toronto, ON, M4X 1M5	43.671593	-79.375083	4500.0
661	3	2.0	0	Salvador Allende Ct, Toronto, ON, M6G 0A3	43.672327	-79.428726	4625.0
654	1	1.0	0	80 Blue Jays Way, Toronto, ON M5V 2G3, Canada	43.645297	-79.392397	4700.0
941	3	2.0	0	14 York St, Toronto, ON M5J 0B1, Canada	43.641908	-79.381780	4900.0
1043	3	3.0	0	397 Front St W, Toronto, ON M5V 3S1, Canada	43.642569	-79.393460	4900.0
922	3	2.0	0	, toronto M5V 3z4 ON, Canada	43.641012	-79.394948	6000.0
845	2	3.0	0	180 University Ave, Toronto, ON M5H 0A2, Canada	43.648953	-79.385768	6500.0
1096	3	2.0	0	21 Widmer St, Toronto, ON M5V 0B8, Canada	43.647226	-79.391100	8000.0
952	2	2.5	0	311 Bay St, Toronto, ON M5H 4G5, Canada	43.649783	-79.380440	9750.0
917	2	1.0	0	, TORONTO M4T 1P3 ON, Canada	43.690463	-79.381576	36900.0
129	1	1.0	0	101 Charles St, TORONTO, ON, M4Y 1V2	43.669593	-79.380580	535000.0

Create a new dataframe without outliers

In [171]:
```python
# Remove out outliers
df_withOut_ol = df_cleaned.query("Price >= @lower_bound & Price <= @upper_bou
df_withOut_ol.head()
```

Out[171]:

	Bedroom	Bathroom	Den	Address	Lat	Long	Price
0	2	2.0	0	3985 Grand Park Drive, 3985 Grand Park Dr, Mis...	43.581639	-79.648193	2450.0
1	1	1.0	1	361 Front St W, Toronto, ON M5V 3R5, Canada	43.643051	-79.391643	2150.0
2	1	1.0	0	89 McGill Street, Toronto, ON, M5B 0B1	43.660605	-79.378635	1950.0
3	2	2.0	0	10 York Street, Toronto, ON, M5J 0E1	43.641087	-79.381405	2900.0
4	1	1.0	0	80 St Patrick St, Toronto, ON M5T 2X6, Canada	43.652487	-79.389622	1800.0

In [172]:

```
# Inspect updated data statistics
df_withOut_ol.describe()
```

Out[172]:

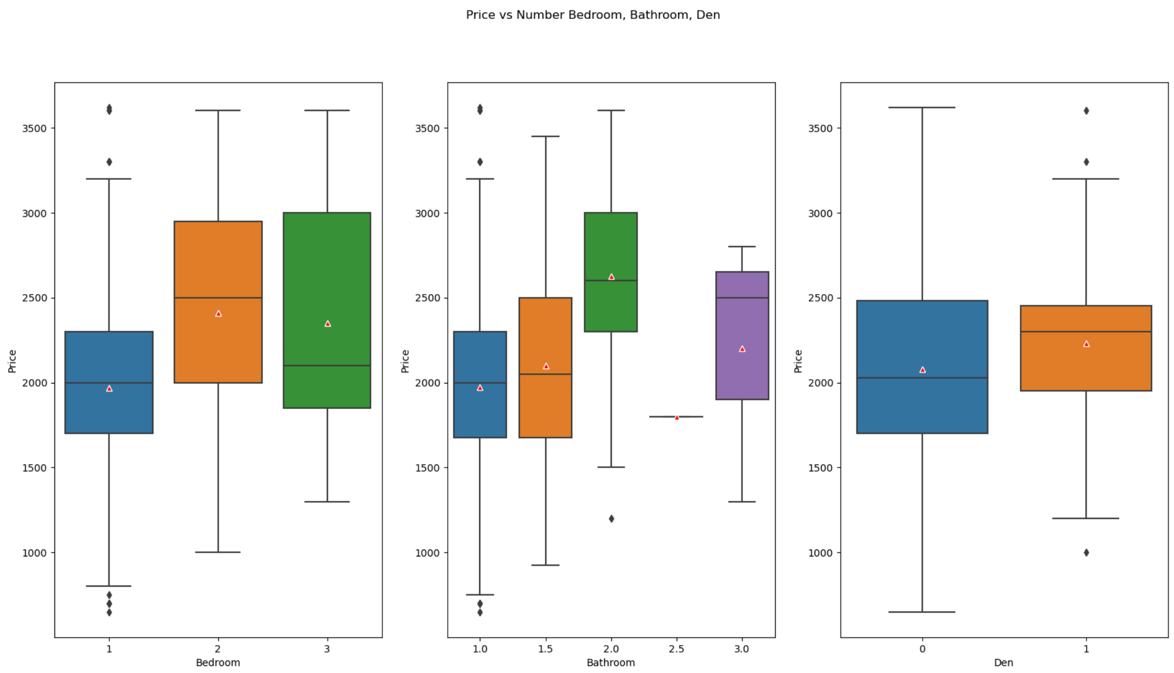
	Bedroom	Bathroom	Den	Lat	Long	Price
count	777.000000	777.000000	777.000000	777.000000	777.000000	777.000000
mean	1.338481	1.214929	0.160875	43.693862	-79.468836	2102.487773
std	0.537246	0.412602	0.367652	0.539526	1.616142	578.116565
min	1.000000	1.000000	0.000000	42.985767	-114.082215	650.000000
25%	1.000000	1.000000	0.000000	43.641579	-79.414786	1750.000000
50%	1.000000	1.000000	0.000000	43.652058	-79.387374	2100.000000
75%	2.000000	1.000000	0.000000	43.667817	-79.376562	2450.000000
max	3.000000	3.000000	1.000000	56.130366	-73.576385	3620.000000

Visualize and Analyze

Use boxplot to visualize the `Price` distibution againts different variables - `Bedroom` , `Bathroom` , and `Den` .

In [173]:

```
# Boxplots - Price vs Number Bedroom, Bathroom, Den
fig, axes = plt.subplots(1, 3, figsize=(20, 10))
fig.suptitle("Price vs Number Bedroom, Bathroom, Den")
meanpropsStyle = dict(markerfacecolor="red",markeredgecolor="white")
sns.boxplot(ax=axes[0], data=df_withOut_ol, x=df_withOut_ol.Bedroom, y=df_wit
            , showmeans=True
            , meanprops=dict(markerfacecolor="red",markeredgecolor="white"))
sns.boxplot(ax=axes[1], data=df_withOut_ol, x=df_withOut_ol.Bathroom, y=df_wi
            , showmeans=True
            , meanprops=meanpropsStyle)
sns.boxplot(ax=axes[2], data=df_withOut_ol, x=df_withOut_ol.Den, y=df_withOut
            , showmeans=True
            , meanprops=meanpropsStyle)
plt.show()
```

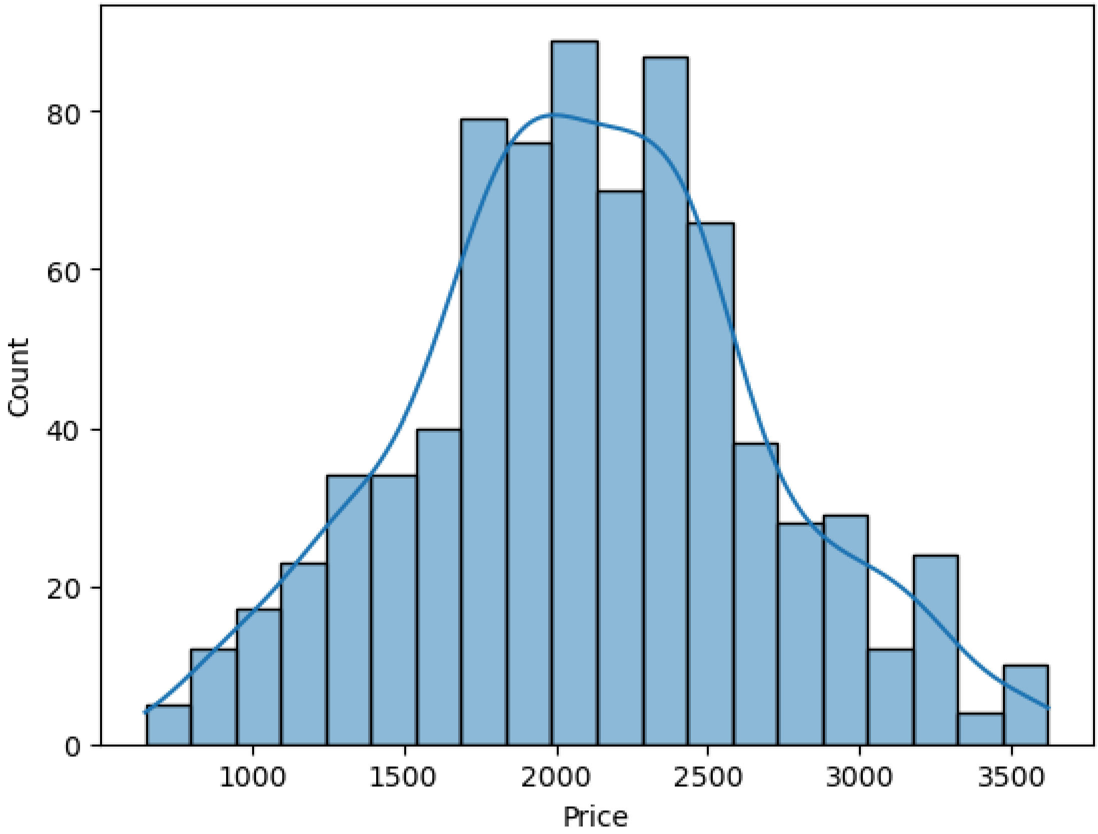


The boxplot shows as that:

- Price varies widely in any of the three variables. Which would mean that neither of these variables are reliable factors to price.
- Having 2 bathrooms increases mean and median price.
- There seems to have no significant advance in having a den.

In [174]:

```
# Histogram of Price - without outliers
sns.histplot(x=df_withOut_ol.Price, kde=True);
```



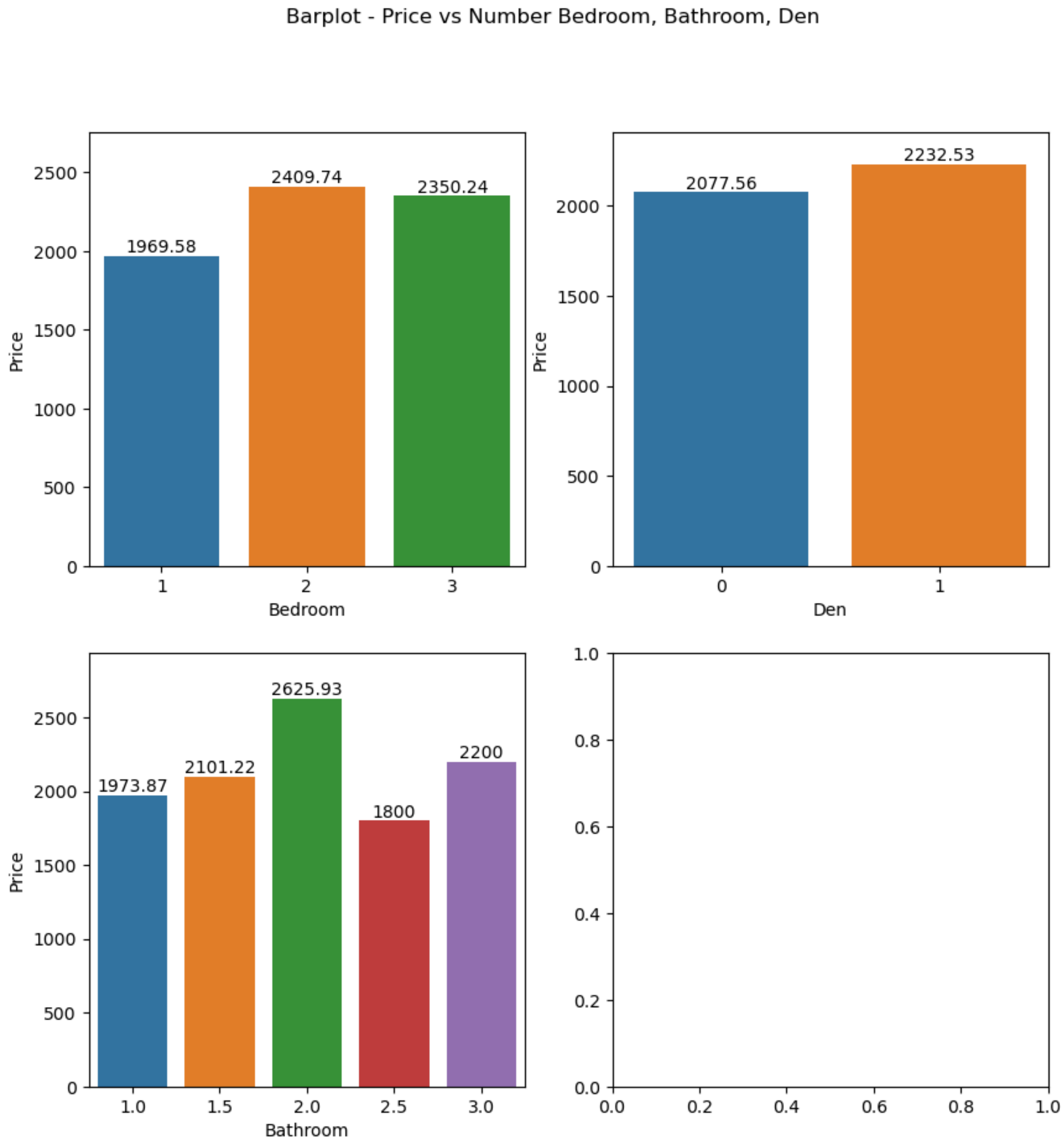
The price data looks normally distributed after removing the outliers.

In [175]:

```
# Barplot - Price vs Number Bedroom, Bathroom, Den
fig, axes = plt.subplots(2, 2, figsize=(10, 10))
fig.suptitle("Barplot - Price vs Number Bedroom, Bathroom, Den")

g1 = sns.barplot(ax=axes[0,0], data=df_withOut_ol, x=df_withOut_ol.Bedroom, y
g1.bar_label(g1.containers[0])
g2 = sns.barplot(ax=axes[1,0], data=df_withOut_ol, x=df_withOut_ol.Bathroom,
g2.bar_label(g2.containers[0])
g3 =sns.barplot(ax=axes[0,1], data=df_withOut_ol, x=df_withOut_ol.Den, y=df_w
g3.bar_label(g3.containers[0])

plt.show()
```



The barplot confirms some observations from our boxplot.

- 2 bathroom units has the hights average price.
- A den has little impact on price.

It also shows that higher number of `Bedroom` or `Bathroom` does not directly translate to higher `Price`

Visualize the most correlated variables in one plot

Most correlated variables - `Price` , `Bedroom` , `Bathroom`

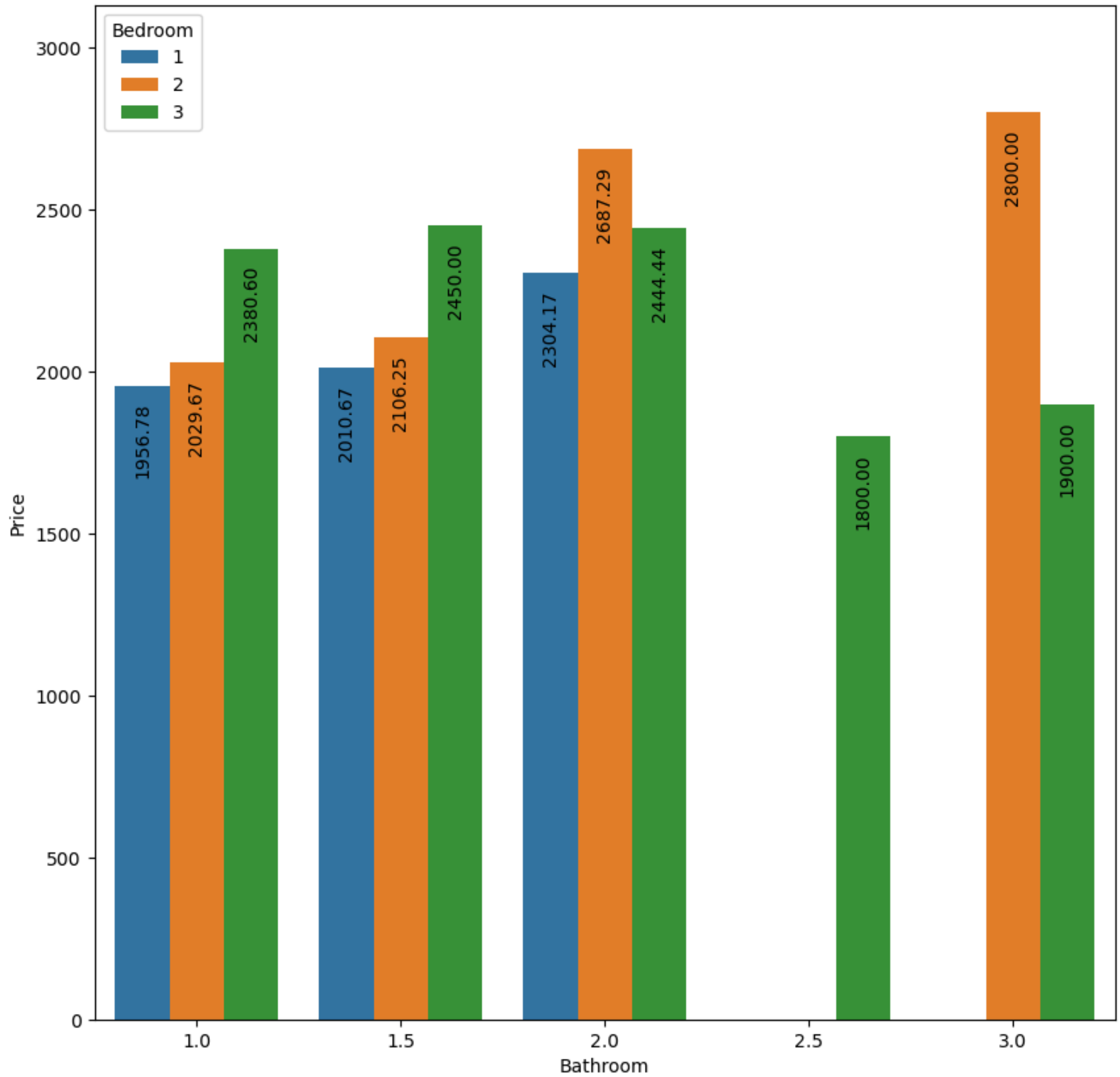
In [176]:

```
# Barplot - Price vs Number Bedroom, Bathroom
fig, axes = plt.subplots(1, 1, figsize=(10, 10))
fig.suptitle("Barplot - Price vs Number Bathrooms and Bedrooms")

g1 = sns.barplot(ax=axes, data=df_withOut_ol
                 , x=df_withOut_ol.Bathroom
                 , y=df_withOut_ol.Price, errwidth=0, hue="Bedroom")
# display value as labesl on each bar
for p in g1.patches:
    g1.annotate(format(p.get_height(), '.2f')
                , (p.get_x() + p.get_width() / 2., p.get_height())
                , ha = 'center', va = 'center'
                , rotation = 90
                , xytext = (0, -30)
                , textcoords = 'offset points')

plt.show()
```

Barplot - Price vs Number Bathrooms and Bedrooms



The multi-variable boxplot above show that:

- Both 1 and 2 price consistently increases with the increase in the number of bathrooms.

- But for 3 bedroom units, those with 1.0, 1.5,2.0 bathrooms are priced higher than those with 2.5 and 3.0 bathrooms.

Creating Correlation matrix with Heatmap

In [177]:
```
corr = df_withOut_ol.corr()
```

In [178]:
```
df_withOut_ol.corr().style.background_gradient(cmap='coolwarm')
```

Out[178]:

	Bedroom	Bathroom	Den	Lat	Long	Price
Bedroom	1.000000	0.595724	-0.276040	-0.002073	-0.015260	0.322933
Bathroom	0.595724	1.000000	-0.096557	0.021219	-0.040010	0.419152
Den	-0.276040	-0.096557	1.000000	0.069554	-0.040159	0.098554
Lat	-0.002073	0.021219	0.069554	1.000000	-0.826082	-0.040747
Long	-0.015260	-0.040010	-0.040159	-0.826082	1.000000	-0.021527
Price	0.322933	0.419152	0.098554	-0.040747	-0.021527	1.000000

Creating Covariance matrix

In [179]:
```
df1 = df_withOut_ol[['Lat', 'Long']]
```

In [180]:
```
print(df1)
```

```
            Lat       Long
0     43.581639 -79.648193
1     43.643051 -79.391643
2     43.660605 -79.378635
3     43.641087 -79.381405
4     43.652487 -79.389622
...         ...        ...
1119  43.325233 -79.802182
1120  43.445426 -79.736833
1121  43.683386 -79.309409
1122  43.653636 -79.380873
1123  43.669931 -79.375463

[777 rows x 2 columns]
```

In [181]:
```
df1.corr().round(2)
```

Out[181]:

	Lat	Long
Lat	1.00	-0.83
Long	-0.83	1.00

In [182]:
```
tb1 = df1.cov().round(2)
tb1
```

Out[182]:

	Lat	Long
Lat	0.29	-0.72
Long	-0.72	2.61

In [183]:
```
Total_Varience = tb1.loc['Lat','Lat'] + tb1.loc['Long','Long']
print(Total_Varience)
```

```
2.9
```

In [184]:
```
Long_Ratio = tb1.loc['Long','Long']/Total_Varience
print(Long_Ratio*100)
```

```
90.0
```

In [185]:
```
Lat_Ratio = tb1.loc['Lat','Lat']/Total_Varience
print(Lat_Ratio*100)
```

```
10.0
```

Normalizatin of dataset

In [186]:
```
df_withOut_ol.columns
```

Out[186]:
```
Index(['Bedroom', 'Bathroom', 'Den', 'Address', 'Lat', 'Long', 'Price'], dty
pe='object')
```

In [187]:
```
df_new = df_withOut_ol[['Bedroom', 'Bathroom', 'Den','Lat', 'Long', 'Price']]
```

In [188]:
```
print(df_new)
```

```
      Bedroom  Bathroom  Den        Lat       Long   Price
0           2       2.0    0  43.581639 -79.648193  2450.0
1           1       1.0    1  43.643051 -79.391643  2150.0
2           1       1.0    0  43.660605 -79.378635  1950.0
3           2       2.0    0  43.641087 -79.381405  2900.0
4           1       1.0    0  43.652487 -79.389622  1800.0
...       ...       ...  ...        ...        ...     ...
1119        3       1.0    0  43.325233 -79.802182  3000.0
1120        1       1.0    0  43.445426 -79.736833  1200.0
1121        1       1.0    0  43.683386 -79.309409  1800.0
1122        2       1.0    0  43.653636 -79.380873  2200.0
1123        1       1.0    0  43.669931 -79.375463  2150.0

[777 rows x 6 columns]
```

In [189]:
```
!pip install scikit-learn
```

```
Defaulting to user installation because normal site-packages is not writeabl
e
Requirement already satisfied: scikit-learn in d:\programdata\anaconda3\lib
\site-packages (1.0.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in d:\programdata\anacon
da3\lib\site-packages (from scikit-learn) (2.2.0)
Requirement already satisfied: joblib>=0.11 in d:\programdata\anaconda3\lib
\site-packages (from scikit-learn) (1.1.0)
Requirement already satisfied: scipy>=1.1.0 in d:\programdata\anaconda3\lib
\site-packages (from scikit-learn) (1.9.1)
Requirement already satisfied: numpy>=1.14.6 in d:\programdata\anaconda3\lib
\site-packages (from scikit-learn) (1.21.5)
```

In [190]:
```
from sklearn.preprocessing import MinMaxScaler
```

In [191]:
```
scaler = MinMaxScaler()
```

In [192]:
```
normalized_data=scaler.fit_transform(df_new)
```

In [193]:
```
normalized_df = pd.DataFrame(normalized_data
                            , columns = ['Bedroom', 'Bathroom', 'Den','Lat',
```

In [194]:
```python
print(normalized_df)
```

```
     Bedroom  Bathroom  Den       Lat      Long     Price
0        0.5       0.5  0.0  0.045332  0.850100  0.606061
1        0.0       0.0  1.0  0.050004  0.856434  0.505051
2        0.0       0.0  0.0  0.051340  0.856755  0.437710
3        0.5       0.5  0.0  0.049855  0.856687  0.757576
4        0.0       0.0  0.0  0.050722  0.856484  0.387205
..       ...       ...  ...       ...       ...       ...
772      1.0       0.0  0.0  0.025826  0.846299  0.791246
773      0.0       0.0  0.0  0.034969  0.847912  0.185185
774      0.0       0.0  0.0  0.053073  0.858464  0.387205
775      0.5       0.0  0.0  0.050809  0.856700  0.521886
776      0.0       0.0  0.0  0.052049  0.856834  0.505051

[777 rows x 6 columns]
```

In [195]:
```python
normalized_df.corr().style.background_gradient(cmap='coolwarm')
```

Out[195]:

	Bedroom	Bathroom	Den	Lat	Long	Price
Bedroom	1.000000	0.595724	-0.276040	-0.002073	-0.015260	0.322933
Bathroom	0.595724	1.000000	-0.096557	0.021219	-0.040010	0.419152
Den	-0.276040	-0.096557	1.000000	0.069554	-0.040159	0.098554
Lat	-0.002073	0.021219	0.069554	1.000000	-0.826082	-0.040747
Long	-0.015260	-0.040010	-0.040159	-0.826082	1.000000	-0.021527
Price	0.322933	0.419152	0.098554	-0.040747	-0.021527	1.000000